Essays on banking risk and access to credit

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by

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Acknowledgments

It is not because things are difficult that we do not dare, it is because we do not dare that they are difficult.

Seneca

Writing a PhD dissertation is usually a long and somewhat painful process. However, I was lucky enough to be surrounded by extraordinary people that made this process much smoother. This is the moment to acknowledge their contribution.

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CHAPTER 1

1 Introduction

In this dissertation I explore several dimensions of risk in banking, while also considering its implications on firms' access to credit. The global economic and financial crisis made clear that a stable and well-functioning banking system is a key pillar of economic growth. Against this background, in the following four chapters of this dissertation I try to shed some light on issues that may critically influence the stability of the financial system and, ultimately, of the economy.

First, in Chapter 2[1], I consider the role of strategic interactions in bank risk taking, focusing on liquidity risk. Banks individually optimize their liquidity risk management, often neglecting the externalities generated by their choices on the overall risk of the financial system. This is the main argument to support the regulation of liquidity risk. However, there may be incentives, related for instance to the role of the lender of last resort, for banks to optimize their choices not strictly at the individual level, but engaging instead in collective risk taking strategies, which may intensify systemic risk. In this chapter, I

[1] This chapter is based on joint work with Moshe Kim.

look for evidence of such herding behaviors, with an emphasis on the period preceding the global financial crisis. I find strong and robust evidence of peer effects in banks' liquidity risk management, even after adequately controlling for potential endogeneity problems associated with the estimation of peer effects. This result suggests that incentives for collective risk taking behaviors may play a role in banks' choices, thus calling for a macroprudential approach to liquidity risk regulation.

In Chapter 3[2], I explore another dimension of bank risk, by examining the influence of macroeconomic conditions on credit risk. Indeed, understanding if credit risk is driven mostly by idiosyncratic firm characteristics or by systematic factors is an important issue for the assessment of financial stability. By exploring the links between credit risk and macroeconomic developments, I observe that in periods of economic growth there may be some tendency towards excessive risk-taking. Using an extensive dataset with detailed information for more than 30,000 firms, I show that default probabilities are influenced by several firm-specific characteristics. When time-effect controls or macroeconomic variables are also taken into account, the results improve substantially. Hence, though the firms' financial situation has a central role in explaining

[2]This chapter is based on Bonfim, D. (2009), Credit risk drivers: evaluating the contribution of firm level information and macroeconomic dynamics, Journal of Banking and Finance, 33(2), 2009, pp. 281-299.

default probabilities, macroeconomic conditions are also very important when assessing default probabilities over time.

In Chapter 4[3], I examine a related issue. Though there is an extensive literature on why firms default, there is surprisingly scarce evidence about what happens to firms after they default. In this chapter I investigate what happens to firms after they default on their bank loans. I approach this question by establishing a set of stylized facts concerning the evolution of corporate default and its resolution, focusing on access to credit after default. Using a unique dataset from Portugal, I observe that half of the corporate default episodes last 5 quarters. Most firms continue to have access to credit immediately after resolving default, though only a minority has access to new loans. Firms have more difficulties in regaining access to credit if they are small, if their default was long and severe, if they borrow from only one bank or if they default with their main lender. Further, half of the defaulting firms record another default in the future. I observe that firms with repeated defaults are, on average, smaller and experience longer and more severe defaults.

Finally, in the last chapter[4], I examine another common event in banking,

[3]This chapter is based on joint work with Daniel Dias and Christine Richmond, published as Bonfim, D., D. Dias and C. Richmond (2012), What happens after corporate default? Stylized facts on access to credit, Journal of Banking and Finance, 36(7), 2012, pp. 2007-2025.

[4]This chapter is based on joint work with Pedro Pita Barros, Moshe Kim and Nuno Martins, published as Barros, P.P., D. Bonfim, M. Kim and N. Martins (2013), Counterfactual

which may affect the stability of the banking system, as well as firms' and households' access to credit. Indeed, bank merger waves may generate structural changes in the equilibrium of credit markets, thereby changing prices and quantities in these markets, with important implications on competition. I derive a counterfactual analysis of banks mergers, combining the pre-merger equilibrium setting with post-merger environmental characteristics, while accounting for endogenously propagated changes in market structure. Using this procedure I am able to estimate the effects on loan flows and interest rates that would have been observed if the pre-merger equilibrium was not altered. Results are obtained for firms, households and banks inside and outside the merging circles separately. I find that mergers increased firms' access to credit, but had an opposite effect on households and led to a widespread decrease in interest rates.

In sum, this dissertation addresses several dimensions of risk in banking. In Chapter 2 I analyze what is perhaps the most critical dimension of banking risk: the funding liquidity risk that is intrinsically associated with banks' key functions of liquidity creation and maturity transformation. In Chapters 3 and 4 I deal with credit risk, another key dimension of risk in banks, which often leads to sizeable losses. Finally, in Chapter 5 I assess how structural changes

Analysis of Bank Mergers, Empirical Economics, forthcoming.

may affect banks' behaviors in the loan market.

By definition, there cannot be banks without some type of risk-taking. Indeed, banks need to take risks to finance households and firms. In this dissertation, I also explore different aspects of access to credit, most notably in Chapter 4, in which I analyze what happens after corporate default (the determinants of which are analyzed in Chapter 3). To some extent, this issue is also addressed in Chapter 5, where I assess how changes in market structure affect loan flows and interest rates of different banks.

CHAPTER 2

2 Liquidity risk in banking: is there herding?

2.1 Introduction

Banks create liquidity in an economy, funding illiquid assets (such as loans) with liquid liabilities (such as deposits), as discussed by Berger and Bouwman (2009) and Bouwman (2013)[5]. This basic intermediation role of banks relies on a maturity mismatch between assets and liabilities, making them exposed to bank runs or, more generally, to funding liquidity risk. There is a vast and prominent theoretical literature on this problem. Diamond and Dybvig (1983) and Bryant (1980) provided the pillars for the analysis of banks' liquidity risk and bank runs, while other very relevant contributions include Klein (1971), Calomiris and Kahn (1991), Diamond and Rajan (2000, 2001a and 2001b), Allen and Gale (2004a, 2004b), and, more recently, Wagner (2007a) or Ratnovski (2009). However, there is surprisingly scarce empirical evidence on banks' maturity mismatches and funding liquidity risk.

In this paper, we contribute to fill in this gap by empirically analyzing the

[5]This chapter reflects joint work with Moshe Kim.

way banks manage their liquidity risk. More specifically, we analyze the determinants of banks' liquidity risk management choices, explicitly considering potential strategic interactions among banks. This issue has relevant policy implications, as banks may have incentives to engage in collective risk-taking strategies when there is a strong belief that a (collective) bailout is possible (Farhi and Tirole, 2012, Acharya and Yorulmazer, 2007, Acharya et al, 2013). When other banks are taking more risk, a given bank may be encouraged to pursue similar strategies if its managers believe they are likely to be rescued in case of distress. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit commitment of the lender of last resort. Hence, these risk-taking strategies may be mutually reinforcing in some circumstances. This collective behavior transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

The first step in our analysis is to provide detailed empirical evidence on banks' liquidity risk management. We begin by discussing how to measure banks' liquidity risk, as several indicators may be relevant to quantify how exposed to this risk is an institution (Tirole, 2011). Subsequently, using a panel dataset of European and North-American banks for the period 2002-2009, we analyze which factors may be relevant in explaining why some banks adopt a globally prudent behavior in managing the liquidity risk underlying their financial intermediation functions, whereas others engage in more aggressive risk-taking strategies. We find that when banks become larger and more profitable, they tend to adopt riskier liquidity strategies, most notably if they have a more traditional intermediation profile. In turn, when banks record larger net interest margins and better cost-efficiency ratios, they are generally less risky in their liquidity management. We cannot find empirical evidence of any relationship between capital and liquidity ratios.

Next, in order to search for evidence on collective risk taking behaviors in liquidity risk management, we compute a simple measure of herd behavior, based on Lakonishok et al (1992). Our results suggest that there was some herding in the pre-crisis period, reflected in a global deterioration of liquidity indicators.

Nevertheless, this herding measure is clearly insufficient to fully identify strategic interactions, as many factors may be driving the results. A multivariate setting allows to consider this issue in a more integrated way, through the estimation of the impact of peer effects (other banks' liquidity choices) on the liquidity indicators of each bank, while controlling for other potentially relevant explanatory variables. Using this approach, we find strong evidence of peer effects in liquidity risk management.

However, it is important to note that the empirical estimation of these peer effects amongst banks raises some econometric challenges. As discussed by Manski (1993), the identification of endogenous and exogenous effects is undermined by the reflection problem associated with the reverse causality of peer effects. In other words, if we argue that peers' choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers. Our solution to this critical identification problem relies on the use of an instrument, which has to be orthogonal to systematic or herding effects (Leary and Roberts, 2013). Specifically, the instrument used for the peer effects is the predicted values of liquidity indicators of peer banks used in the regressions of the determinants of liquidity indicators. Thus, the predicted values depend on the characteristics of the banks in the peer group. These predicted values depend only on observable bank characteristics and should therefore be orthogonal to herding effects. In other words, the predicted value of the liquidity indicators of peer banks should not directly affect the liquidity indicators of bank i at time t, as these predicted values are based solely on observable bank characteristics. By controlling also for time fixed-effects, we are able to orthogonalize all systematic and common shocks to banks. Furthermore, we control for country-year fixed effects. This allows to control for all country-specific time-varying shocks, such as changes in macroeconomic and financial conditions, as well as changes in the regulatory environment. The benchmark peer group is the banks operating in the same country in each year, as these are the banks that are more likely to share common beliefs about the likelihood of being bailed out by their common lender of last resort.

After adequately dealing with the peer effect estimation, we obtain strong and consistent evidence of collective risk-taking behaviors in liquidity risk management, under a wide set of specifications. These results have relevant policy implications: liquidity risk is usually regulated from a microprudential perspective, but our results show that a macroprudential approach to the regulation of systemic liquidity risk should not be disregarded. Given this, even though the new Basel III package on liquidity risk is a huge step forward in the regulation of liquidity risk, additional macroprudential policy tools may need to be considered, as the new regulation is still dominantly microprudential. For instance, macroprudential authorities may consider imposing tighter liquidity regulation or limits to certain types of exposures, in order to mitigate contagion and systemic risks, thereby providing the correct incentives to minimize negative externalities.

The contribution of our paper is manyfold. Even though the theoretical literature provides many relevant insights regarding banks' liquidity risk, there is scarce empirical evidence on banks' liquidity risk management. Furthermore, we focus on a period of particular relevance, as there is an extensive discussion regarding excessive risk-taking in the years preceding the global financial crisis. We provide detailed empirical evidence on the determinants of liquidity risk, and, more importantly, we extend the analysis by focusing on strategic interactions and herding behavior. In this respect, we consider not only traditional herding measures, but we also make an effort to provide a correct and rigorous econometric treatment for the endogeneity of peer effects in a multivariate setting. Finally, our results provide important insights for policy makers, most notably in what concerns the macroprudential regulation of systemic liquidity risk.

This chapter is organized as follows. We begin by reviewing the expanding literature on bank's funding liquidity risk and its regulation, in Section 2.2. In Section 2.3 we discuss several indicators of banks' liquidity risk and characterize the dataset used for the empirical analysis, including an overview of banks' liquidity and funding choices in the run up to the recent global financial crisis. In Section 2.4 we analyze how banks manage their liquidity risk and in Section 2.5 we address the most relevant question in our paper:

do banks take into account peers' liquidity strategies when making their own choices on liquidity risk management? More importantly, was this relevant to the build-up of global risks in the financial system that eventually led to the Great Recession? In Section 2.6 we summarize our main findings and discuss their policy implications.

2.2 Related literature and regulation

Over recent years, banks became increasingly complex institutions, being exposed to an intertwined set of risks. The 2008 financial crisis provided a painful illustration of how severe these risks can be and how they can seriously affect the real economy. However, regardless of how complex banks have become, there is an intrinsic risk that lies deep in their core function: banks are special due to their unique intermediation role. They grant loans to entrepreneurs and consumers, providing them with the necessary liquidity to finance their investment and consumption needs. However, banks use only a limited amount of their own resources to grant this funding. Capital requirements on risky assets constitute a binding constraint for the minimum amount of own funds needed. Most of the funds used by banks are associated with liabilities to third parties. Traditionally, these liabilities would take the form of deposits. These liquid claims allow consumers to intertemporally optimize their consumption preferences, but leave banks exposed to the risk of bank runs, as shown by Diamond and Dybvig (1983). However, the risk of runs acts as a disciplining device on banks (Diamond and Rajan, 2001b), given that depositors (Calomiris and Kahn, 1991), as well as borrowers (Kim et al, 2005), have incentives to monitor the risks taken by banks.

Through time, banks gained access to a more diversified set of liabilities to fund their lending activities, thus being exposed not only to traditional runs from depositors, but also to the drying up of funds in wholesale markets, as discussed by Huang and Ratnovski (2011) or Borio (2010), amongst many others.

The increased reliance on wholesale funding makes the relationship between funding and market liquidity risk much stronger, as discussed by Brunnermeier and Pedersen (2009), Cai and Thakor (2009), Drehmann and Nikolau (2009), Freixas et al (2011), Krishnamurthy (2010), Milne (2008), Strahan (2008), and Tirole (2011). Funding and market liquidity risk are two distinct concepts: whereas the former can be broadly defined as the risk of losing access to funding (through the form of runs or refinancing risk), the latter can be defined as the ability to sell assets without disrupting their markets prices (see, for instance, Cai and Thakor, 2009, Milne, 2008, or Tirole, 2011). Brunnermeier and Pedersen (2009) and Brunnermeier (2009) show that under certain conditions market and funding liquidity risk may be mutually reinforcing, leading to liquidity spirals, most notably when there are systemic risk concerns. For example, if a bank is not able to rollover some of its debt, it may be forced to sell some of its assets to obtain liquidity. However, the fire sale of assets will depress asset prices and shrink banks' assets, given that they are marked-to-market, thus making access to funding even more constrained (Nikolau, 2009).

Given this, even though banks are the main providers of liquidity to the economy (Berger and Bouwman, 2009; Diamond and Dybvig, 1983), they have to adequately manage the liquidity risk underlying their balance sheet structure, as their maturity transformation function makes them inherently illiquid. To alleviate the maturity gap between assets and liabilities, banks can hold a buffer of liquid assets (Acharya et al, 2011, Acharya et al, 2013, Allen and Gale, 2004a and 2004b, Bouwman, 2013, Calomiris et al, 2013, Farhi et al, 2009, Feinman, 1993, Gale and Yorulmazer, 2013, Rochet and Vives, 2004, Tirole, 2011, and Vives, 2011). However, holding liquid assets is costly, given that they provide lower returns than illiquid assets. Moreover, holding a liquidity buffer may also be inefficient, as it limits banks' ability to provide liquidity to entrepreneurs and consumers. Hence, even though banks have some incentives to hold a fraction of liquid assets (in the form of cash, short term assets or government bonds, for instance), these buffers will hardly ever be sufficient to fully insure against a bank run or a sudden dry up in wholesale markets.

Against this setting, regulation becomes necessary to mitigate some of these risks (Bouwman, 2013). One justification for the need to regulate liquidity risk is related to the fact that banks do not take into account the social optimum when they optimize the relationship between risk and return. However, a bank failure may constitute a huge externality on other banks and, ultimately, on the whole economy. This risk is exacerbated by the fact that liquidity shocks are events with very low probability (though with potentially very high impact), thus making it easy to overlook them during good periods. Allen and Gale (2004a, 2004b) show that liquidity risk regulation is necessary when financial markets are incomplete, though emphasizing that all interventions inevitably create distortions. Furthermore, Rochet (2004) argues that banks take excessive risk if they anticipate that there is a high likelihood of being bailed-out in case of distress. Ex-ante regulation of banks' liquidity may mitigate this behavior. Many other authors share the view that liquidity risk regulation is necessary (Acharya et al, 2011, Brunnermeier et al, 2009, Cao and Illing, 2010, Gale and Yorulmazer, 2013, Holmstrom and Tirole, 1998, and Tirole, 2011, for example).

However, a consensus is far from being reached on the optimal regulatory framework to mitigate liquidity risk, both academically and politically, though a remarkable progress has been achieved during the last few years. Traditionally, reserve requirements on bank deposits were the main tool for liquidity risk management, though they also play an important role in the implementation of monetary policy (Robitaille, 2011). More importantly, deposit insurance is by now broadly recognized as an important tool in preventing depositors' bank runs[6]. Explicit deposit insurance can prevent runs on bank deposits, as shown by Diamond and Dybvig (1983)[7]. However, deposit insurance can only be efficient in minimizing the likelihood of bank runs by depositors. For instance, Bruche and Suarez (2010) show that deposit insurance can cause a freeze in interbank markets, when there are differences in counterparty risk. Indeed, deposit insurance is not sufficient to forestall all liquidity-related risks and may generate moral hazard (Ioannidou and Penas, 2010, Martin, 2006). Given the increased diversification of banks' funding sources (Strahan, 2008), other regulatory mechanisms must be envisaged to ensure the correct alignment of incentives. The dispersion of creditors and the diversification of risks

[6] During the recent crisis, many governments in advanced economies decided to increase the coverage of their national deposit insurance schemes to avoid panic runs.

[7] However, Demirgüç-Kunt and Detagriache (2002) find that explicit deposit insurance increases the likelihood of banking crises, using data for 61 countries. This empirical result is stronger when bank interest rates are deregulated, the institutional environment is weak and the scheme is run or funded by the government.

and activities undertaken by banks make this issue even more complex.

A few recent and ongoing discussions have suggested the possibility of further increasing capital requirements to also include liquidity risks[8] (Brunnermeier et al, 2009[9]). However, there are several opponents to this view and a consensus has emerged on the need to regulate explicitly liquidity risk. As argued by Ratnovski (2013), funding liquidity risk is in part related to asymmetric information on banks' solvency. Increasing solvency without reducing the asymmetric information problem would not reduce refinancing risk. Perotti and Suarez (2009) have also put forth a proposal regarding a liquidity insurance mechanism to avoid systemic crises.

Many authors discuss the importance of holding a liquidity buffer. In a recent paper, Ratnovski (2009) discusses the trade-offs between imposing quantitative requirements on banks' liquidity holdings and improving the incentive scheme in lender of last resort policies. This author argues that quantitative requirements can achieve the optimal liquidity level, but not without imposing costs, whereas a lender of last resort policy that takes into account bank capital information may reduce distortionary rents, thus allowing for a more efficient solution. There are many other contributions in the academic litera-

[8] In Basel II, capital requirements were set to explicitly cover credit, market and operational risks, but not liquidity risk.

[9] The model in Diamond and Rajan (2001b) implicitly considers this possibility.

ture pointing to the possibility of imposing minimum holdings of liquid assets (Acharya et al, 2011, Allen and Gale, 2004a and 2004b, Farhi et al, 2009, Gale and Yorulmazer, 2013, Rochet and Vives, 2004, Tirole, 2011, and Vives, 2011). However, Wagner (2007b) shows that, paradoxically, holding more liquid assets may induce more risk-taking by banks. Freixas et al (2011) show that central banks can manage interest rates to induce banks to hold liquid assets, i.e., monetary policy can help to promote financial stability. In turn, Bengui (2010) finds arguments to support a tax on short-term debt, whereas Cao and Illing (2011) show that imposing minimum liquidity standards for banks ex-ante is a crucial requirement for sensible lender of last resort policies. Finally, Diamond and Rajan (2005) and Wagner (2007a) focus on ex-post interventions.

Against this background, the new international regulatory framework will be based on imposing minimum holdings of liquid assets. Globally, liquidity risk regulation was perhaps somewhat overlooked before the global financial crisis, with almost non-existent internationally harmonized rules (Rochet, 2008). However, the role played by funding liquidity during the global financial crisis made clear that a new international regulatory framework was necessary. In December 2010, the Basel Committee disclosed the final version of the international framework for liquidity risk regulation (Basel Committee, 2010), which is an important part of the new Basel III regulatory package. This new regulation provides the necessary incentives for banks to hold adequate liquidity buffers and to avoid over relying on short-term funding. Liquidity risk regulation will be based upon two key indicators: the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The LCR will require banks to hold sufficient high-quality liquid assets to withstand a 30-day stressed funding scenario, being a ratio between the value of the stock of high quality liquid assets in stressed conditions and total net cash outflows, calculated according to scenario parameters defined in the regulation. In turn, the NSFR is a longer-term structural ratio designed to address liquidity mismatches and to encourage an increased reliance on medium and long-term funding, thus increasing the average maturity of banks' liabilities. The NSFR is the ratio between the available and the required amount of stable funding, which should be at least 100%. The two indicators are complementary and ensure that banks hold an adequate pool of liquid assets, while simultaneously adopting a reasonable and prudent maturity mismatch.

Still, when regulation fails to preemptively address risks, there is always the lender of last resort. Bagehot (1837) was amongst the first to acknowledge that such mechanism was a central piece in crisis management[10]. Since then,

[10]"Theory suggests, and experience proves, that in a panic the holders of the ultimate bank reserve (whether one bank or many) should lend to all that bring good securities

the consensus has been to lend freely, usually at penalty rates, to all solvent but illiquid banks (though it is in practice very hard to draw the line between solvency and liquidity problems). The recent financial crisis demonstrated the importance of the lender of last resort. From August 2007 onwards, the freeze in interbank money markets made lending from central banks worldwide crucial[11]. The failure of Lehman Brothers in September 2008 vividly demonstrated the dramatic consequences of a failure of a systemic financial institution[12]. However, the lender of last resort has an intrinsic moral hazard problem (see, for example, Freixas et al, 2004, Gorton and Huang, 2004, Ratnovski, 2009, Rochet and Tirole, 1996, Rochet and Vives, 2004, Wagner, 2007a). This mechanism has to be credible ex-ante to prevent crises. But if the mechanism is in fact credible, banks will know they will be helped out if they face severe difficulties, thus having perverse incentives to engage in excessive risk-taking behaviors. For instance, Gonzales-Eiras (2004) finds that banks' holding of liquid assets decrease when there is a lender of last resort,

quickly, freely, and readily. By that policy they allay a panic; by every other policy they intensify it.", Bagehot (1837).

[11] Lending from central banks during the initial stages of the crisis occurred mainly through monetary policy operations and not through emergency liquid assistance (which corresponds to the function of lender of last resort). For further details and analysis of the freeze in interbank markets in 2007 we refer to Acharya and Merrouche (2012), Afonso et al (2011), Allen and Carletti (2008), Angelini et al (2011), Brunnermeier (2009), and Cornett et al (2011).

[12] Two excellent analyzes of the crisis are Acharya and Richardson (2009) and Brunnermeier et al (2009). Both present a set of proposals to rethink the regulation of the financial system globally.

using a natural experiment in Argentina. This moral hazard problem is further aggravated by systemic behavior[13].

Indeed, when most banks are overtaking risks, each bank manager has clear incentives to herd, instead of leaning against the wind. Ratnovski (2009) argues that, in equilibrium, banks have incentives to herd in risk management, choosing suboptimal liquidity as long as other banks are expected to do the same. These collective risk-taking strategies may be optimal from an individual perspective, as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit bail out commitment of the lender of last resort. These arguments are discussed in detail by Farhi and Tirole (2012), who argue that when banks simultaneously increase their liquidity risk, through larger maturity mismatches, current and future social costs are being created. Given all these market failures, regulation is needed to ensure that these externalities are considered by banks in their liquidity risk management. Nevertheless, the costs and distortions generated by such regulation also need to be taken into account. Acharya and Yorulmazer (2007) and Acharya et al (2013) also discuss bailouts when there are many potentially correlated failures. Acharya et al (2011) consider the

[13] Citigroup's former CEO, Charles Prince, has been repeatedly quoted by saying before August 2007 that "When the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing".

effect of the business cycle on banks' optimal liquidity choices and prove that during upturns banks' choice of liquid assets jointly decreases. In turn, Allen et al (2012) show that when banks make similar portfolio decisions systemic risk increases, as defaults become more correlated. Jain and Gupta (1987) find (weak) evidence on bank herding during a crisis period. Collective risk taking incentives and behaviors are also discussed by Acharya (2009), Acharya and Yorulmazer (2008), Boot (2011), Rajan (2006), Tirole (2011), and Van den End and Tabbae (2012). This emerging evidence on systemic liquidity risk calls for adequate macroprudential instruments that address the sources of such risks, as discussed by Farhi and Tirole (2012), Boot (2011), and Cao and Illing (2010). Nevertheless, most of these conclusions are supported by theoretical results, lacking empirical support. Our paper intends to fill this gap in the literature, by providing empirical evidence of herd behavior in liquidity risk management.

2.3 How to measure liquidity risk?

The maturity transformation role of banks generates funding liquidity risk (Diamond and Dybvig, 1983). As banks' liabilities usually have shorter maturities than those of banks' assets, banks have to repeatedly refinance their assets. This refinancing risk is larger the wider is the mismatch between assets' and liabilities' average maturities. In the run up to the global financial crisis, many banks were engaging in funding strategies that heavily relied on short-term funding (Brunnermeier, 2009 and CGFS, 2010), thus significantly increasing their exposure to funding liquidity risk. Nevertheless, this risk can be mitigated if banks hold a sufficiently large buffer of highly liquid and good quality assets, which they can easily use when hit by unforeseen funding shocks.

In this section, we briefly review several ways to measure funding liquidity risk, which will later be used in our empirical analysis. As discussed by Tirole (2011), liquidity cannot be measured by relying on a single variable or ratio, given its complexity and the multitude of potential risk sources. This section also includes a brief description of the data used in this paper and an overview of banks' liquidity and funding choices in the years preceding the global financial crisis.

2.3.1 Liquidity indicators

An analysis of balance sheet structure can provide an important insight on banks' liquidity risk. More specifically, the ratio between credit granted and deposits taken from customers provides a broad structural characterization of banks' main funding risks. Given that customers deposits are a broadly stable funding source (in the absence of bank runs), those banks that finance most or all of their credit with deposits should, *ceteris paribus*, be less exposed to liquidity risk. In contrast, banks that show a large funding gap, i.e., a very high loan-to-deposit ratio, will be more exposed to this risk, as they will need to rely on wholesale funding markets[14]. Against this background, banks in which wholesale market funding as a percentage of assets is higher will be more sensitive to refinancing risk. This latter risk will be higher the shorter is the maturity of market funding. Hence, the analysis of the balance sheet structure based on the above mentioned liquidity indicators (loan-to-deposit ratio, funding gap or market funding as a percentage of assets) does not allow for a complete assessment of liquidity risk, as these indicators are unable to take into account the maturity mismatch between assets and liabilities.

Another important dimension of funding liquidity risk that became a key issue since the summer of 2007 is the reliance on interbank funding. Interbank markets allow markets to close, by allowing banks with short-term liquidity needs to obtain funds from other banks with temporary excess liquidity. However, after August 2007, unsecured money markets became severely impaired

[14]It is also possible that the mismatch between loans and deposits is financed with more equity, rather than with wholesale funding. If a bank has strong equity ratios and does not rely on wholesale funding, a high loan-to-deposit ratio does not imply strictly higher risk. However, very few banks rely entirely on deposit funding, as most banks approach the interbank market to match short-term mismatches between assets and liabilities and many banks obtain regular funding from debt markets. To control for this interaction between equity and the loan-to-deposit ratio, we control for capital ratios in the multivariate analysis conducted in this paper (see sections 3 and 4).

for a long period (Afonso et al, 2011, Cornett et al, 2011, Brunnermeier, 2009, Allen and Carletti, 2008, and Angelini et al, 2011). Wagner (2007a) shows that the interbank markets may be inefficient in providing liquidity when banks are hit by aggregate liquidity shocks. Against this background, the interbank ratio measured, for instance, as the ratio between interbank assets and interbank liabilities, may also be an important input to the assessment of liquidity risk. In fact, if banks structurally rely on funding from interbank markets, which is usually characterized by very short maturities, they may have severe difficulties in rolling over their debt in periods of distress.

Another important dimension of liquidity risk is related to the buffer of liquid assets held by banks. Refinancing risk may be mitigated if banks hold a comfortable buffer of high quality very liquid assets that they can easily dispose of in case of unexpected funding constraints. In this respect, the ratio of liquid assets to short-term funding also provides important insights into banks' liquidity risk. Even though the available data does not allow to compute the Basel III Liquidity Coverage Ratio (LCR), this liquidity indicator may be taken as a close approximation.

All the above mentioned indicators consider only parts of banks' balance sheets. Hence, a more encompassing analysis of the liquidity of assets and liabilities may be desirable. Ideally, a complete liquidity indicator would rely on the overall liquidity mismatch between assets and liabilities. However, the data necessary for such an indicator is usually not publicly available. Nevertheless, some approximation may be feasible. One interesting approach was suggested by Berger and Bouwman (2009). These authors define liquidity creation as:

$$\begin{aligned} liq\_creation \;=\; & \{1/2 * illiq\_assets + 0 * semi\_liq\_assets - 1/2 * liq\_assets\} \\ & + \{1/2 * liq\_liab. + 0 * semi\_liq\_liab. - 1/2 * illiq\_liab.\} \\ & -1/2 * capital \end{aligned}$$

The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. More liquidity is created when illiquid assets are transformed into liquid liabilities. Of course, liquidity creation is positively related with funding liquidity risk, given that banks that create more liquidity have less liquid assets to meet short-term funding pressures[15].

Ultimately, the Net Stable Funding Ratio (NSFR) included in the Basel III package provides the broadest way to characterize the global liquidity profile of a bank. As mentioned before, the NSFR is the ratio between the avail-

[15] Berger and Bouwman (2009) consider two different measures of liquidity creation. Besides the one presented above, there is another definition that considers off-balance sheet data. Tough the latter definition is more encompassing, capturing better the liquidity created by a bank, the data available in Bankscope does not allow us to compute it for our sample.

able and the required amount of stable funding. The higher this ratio is, the more comfortable is the institution's liquidity position. Though the available data does not allow for the accurate computation of this indicator, a gross approximation is possible.

In sum, given the challenges in measuring funding liquidity risk, our empirical analysis will be based on the analysis of five complementary indicators: the credit to deposit ratio, an interbank ratio, a liquidity ratio, a liquidity creation indicator and a net stable funding ratio, all of them defined in detail in Section 2.3.3. These indicators allow us to capture different dimensions of liquidity risk, including structural balance sheet risks, exposures to short-term funding in interbank markets, the availability of a pool of highly liquid assets to face unexpected shocks, and the magnitude of maturity transformation.

2.3.2 Data

Given that one of our objectives is to assess the extent to which banks take each others' choices into account when managing liquidity risk, it is relevant to consider a sufficiently heterogeneous group of banks. With that in mind, we collect data from Bankscope for the period between 2002 and 2009, thus covering both crisis and pre-crisis years. We collect data on European and North-American banks, selecting only commercial banks and bank holding companies for which consolidated statements are available in universal format, so as to ensure the comparability of variables across countries. Savings and investment banks were not included in the dataset, as they usually have different liquidity risk profiles and funding strategies. Using these filters, we obtain data for almost 3,500 banks during 8 years, for 45 countries[16]. Excluding banks without information on total assets, we obtain 17,643 bank-year observations.

In Table 2.1 we summarize the major characteristics of the banks included in the sample. To avoid having results affected by outliers, all variables were winsorised in their 1st and 99th percentiles. We observe that there is a substantial dispersion in bank size, measured by total assets. The average total capital ratio is 14.5% (12.9% for the median bank). There is also substantial dispersion in banks' profitability, measured both by return on assets and by the net interest margin, and in banks' efficiency, measured by the cost-to-income ratio. Loans represent almost two thirds of the assets of the banks included in the sample, even though the table shows that there are banks with very

[16] These countries are Albania, Andorra, Austria, Belarus, Belgium, Bosnia-Herzegovina, Bulgaria, Canada, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Moldova Republic, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russian Federation, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom, and United States. In Albania, Bosnia-Herzegovina, Liechtenstein, Moldova Republic, Montenegro and San Marino there are less than 10 observations for the entire sample period. Given this, we exclude these five countries from all cross-country analysis.

different specializations, as loans range from 5.1% to 90.6% of banks' assets.

Table 2.1 - Banks' characteristics

	N	mean	min	p25	p50	p75	max
Total assets	17620	21,200	92	295	659	2,183	772,000
Total capital ratio	10211	14.5	7.3	11.3	12.9	15.6	44.5
Tier 1 ratio	9851	12.6	4.7	9.5	11.2	13.9	41.6
Net interest margin	17561	3.7	0.3	3.0	3.8	4.4	10.4
Return on assets	17596	0.9	-4.9	0.5	1.0	1.3	5.1
Cost to income	17510	67.1	27.4	56.7	65.0	74.2	165.1
Net loans to total assets	17509	63.0	5.1	55.1	66.4	75.2	90.6

Notes: Total assets in millions of USD. The total capital and Tier 1 ratios are calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions. These variables are included in the Bankscope database. The statistics presented refer to data after outliers were winsorized.

2.3.3 An overview of banks' liquidity and funding choices in the run up to the global financial crisis and afterwards

In Table 2.2 we summarize the information on liquidity risk for the banks included in the sample. Taking into account our discussion of liquidity indicators in Section 2.3.1, we focus our analysis of liquidity risk on five different indicators: i) *loans to customer deposits*; ii) the *interbank ratio*, defined as the ratio between interbank assets (loans to other banks) and interbank liabilities (loans from other banks, including central bank funding); iii) the *liquidity* *ratio*, defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalents) as a percentage of customer deposits and short-term funding; iv) *liquidity creation* as a percentage of total assets, which is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009); and v) a *Net Stable Funding Ratio*, which is an approximation of the indicator proposed by the Basel Committee. The first three variables are computed in a standardized way in the Bankscope database. The remaining two were computed using balance sheet data (details are presented in the Appendix). In Panel A of Table 2.2 we present summary statistics for these five indicators and in Panel B we depict their evolution during the sample period. In Figures 2.1 to 2.10 we present the empirical distributions of these indicators.

Table 2.2 - Liquidity indicators - summary statistics

Panel A - Global summary statistics

	N	mean	min	p25	p50	p75	max
Loans to customer deposits	17175	94.5	0.0	73.9	88.1	102.7	365.6
Interbank ratio	3599	143.0	0.0	31.8	71.7	168.1	895.2
Liquidity ratio	17494	16.3	1.2	4.2	7.5	16.7	125.6
Liquidity creation	17620	9.1	-35.7	-4.8	4.8	22.1	69.2
NSFR	17618	115.1	27.8	106.7	121.2	129.9	155.1

Panel B - Liquidity indicators over time (mean)

	2002	2003	2004	2005	2006	2007	2008	2009	Total
Loans to customer deposits	84.1	84.9	89.6	93.0	103.1	106.0	107.9	98.7	94.5
Interbank ratio	195.7	172.2	163.2	152.2	143.8	132.2	122.8	122.1	143.0
Liquidity ratio	14.7	13.4	13.7	15.0	20.6	19.7	18.1	19.1	16.3
Liquidity creation	2.7	2.5	3.8	6.9	13.0	13.7	13.9	24.9	9.1
NSFR	122.2	122.6	119.9	116.9	109.4	108.5	108.2	104.5	115.1

Notes: The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. The first three variables in this table are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Appendix. The statistics presented refer to data after outliers were winsorized.

As mentioned above, the ratio between loans and customer deposits is a structural indicator of funding liquidity risk. A ratio above 100% means that the bank has to finance part of its loans with wholesale market funding, which may be more expensive and less stable than customer deposits. The difference between loans and customer deposits is usually referred to as the funding gap. During the last decades, banks have moved from a traditional intermediation paradigm in which most loans were funded through deposits (thus implying loan to deposits ratios not far from 100%) to a new framework of bank funding. As access to wholesale markets became more generalized, banks were able to diversify their funding sources. This had implications on the maturity transformation role of banks. Looking at our sample period, we observe a consistent increase in this ratio, from 84.1 per cent in 2002 to 107.9 per cent in 2008. There is a significant dispersion in the ratios recorded by banks in different countries.

Figure 2.1

Empirical distribution of the ratio between loans and customers deposits

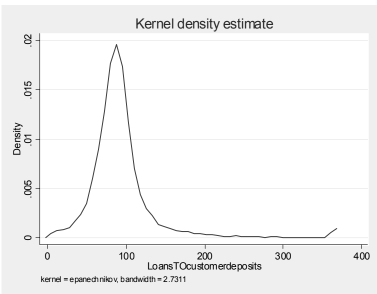
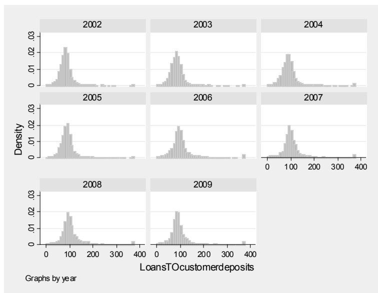


Figure 2.2

Empirical distribution of the ratio between loans and customers deposits - by year



However, this indicator, in and by itself, is insufficient to globally assess the liquidity position of credit institutions. Several limitations of this indicator can be mentioned. First, it is essentially a structural indicator and thus strategic and cyclical changes may take some time to be reflected in the data. Second, the increased use of securitization operations by banks during the last decade undermines to some extent the analysis of this indicator (when banks securitize loans, these are usually removed from their loan books, thus generating a somewhat misleading decrease in the credit to deposit ratio). Finally, this indicator does not take into account the maturity mismatch between assets and liabilities, which is a key element of liquidity risk analysis.

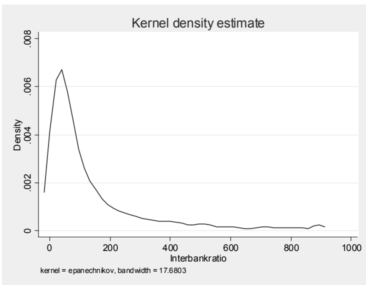
The interbank ratio allows to assess another dimension of bank's funding liquidity risk, evaluating whether banks are net borrowers or net lenders in interbank markets. As we define this indicator as the ratio between loans to other banks and loans from other banks, a ratio above 100% means that a bank is a net lender in interbank markets, thus signaling a more comfortable liquidity position than otherwise.

During our sample period, this ratio decreased gradually, thus implying a deterioration on the average position of banks in these markets. Comparing the interbank positions at the beginning and end of the sample period, some countries recorded a significant decline, whereas others recorded the opposite evolution. All in all, Figure 2.4 clearly illustrates that the dispersion of this ratio decreased markedly during the sample period.

The freeze in interbank markets observed since the financial market turmoil started in August 2007 makes the intertemporal analysis of this ratio more challenging. During most of the global financial crisis, the lack of confidence led to severe disruptions in the functioning of interbank markets. Uncollateralized operations almost ceased to exist during significant periods and high haircuts were imposed on collateralized operations. Thus, there is a clear series break in this indicator from August 2007 onwards, which will be analyzed further ahead. Furthermore, it is important to note that end-of-year data for this ratio may sometimes be subject to some window-dressing, thus not fully reflecting the average values shown throughout the year.

Figure 2.3

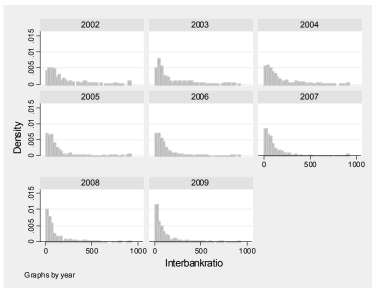
Empirical distribution of the interbank ratio



Note: The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks).

Figure 2.4

Empirical distribution of the interbank ratio - by year

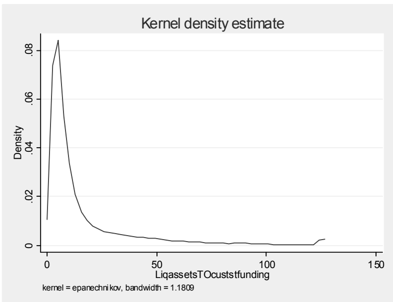


Note: The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks).

Again, the interbank ratio allows for the evaluation of only one dimension of liquidity risk. A more encompassing indicator is the ratio of liquid assets to customer and short-term funding. The lower the ratio, the more challenging it may be for banks to honor their short-term financial commitments. This ratio increased up until the financial turmoil in the summer of 2007. Hence, there does not seem to exist evidence of any dilapidation of the buffer of liquid assets or of a relative increase in short-term funding of European and North-American banks in the run up to the crisis. However, in 2007 and 2008 there was some deterioration in this liquidity ratio, mainly due to the strong growth in customer and short-term funding.

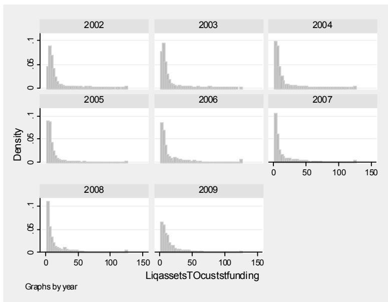
Again, the cross-country dispersion is considerable. For most countries, this ratio shows remarkable volatility during the sample period, as it easily reflects changes in banks' strategic behavior in terms of liquidity risk management.

Figure 2.5
Empirical distribution of the liquidity ratio



Note: The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding.

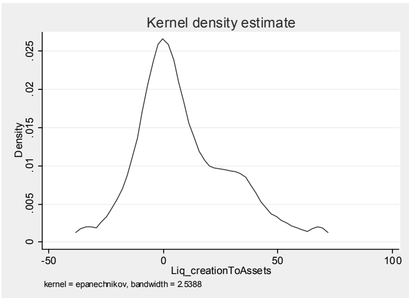
Figure 2.6
Empirical distribution of the liquidity ratio - by year



Notes: The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding.

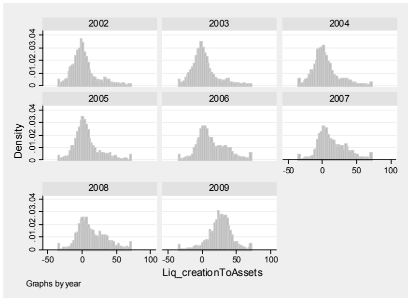
Liquidity creation increased steadily during the sample period, including during the crisis years. Actually, its highest value was recorded in 2009, thus showing that banks continued to create liquidity even during the global financial crisis. However, this also implies that liquidity risk increased during this period, according to this indicator. From all the indicators analyzed, this is the one which presents a distribution closer to the normal, though having a fat right tail.

Figure 2.7
Empirical distribution of the liquidity creation ratio



Note: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. Please see Appendix for further details.

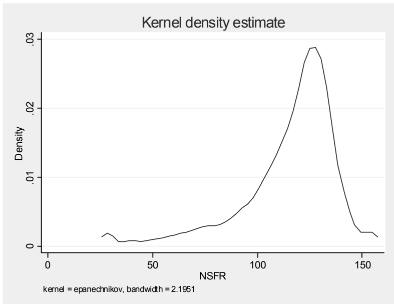
Figure 2.8
Empirical distribution of the liquidity creation ratio - by year



Note: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. Please see Appendix for further details.

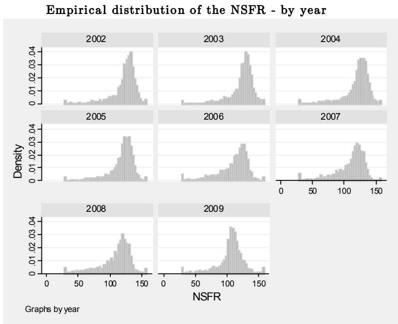
Finally, the NSFR showed some deterioration in the run up to the crisis. It is important to stress that this indicator is a rough approximation of the indicator proposed by the Basel Committee. As such, the 100 per cent minimum threshold defined for this ratio for prudential purposes cannot be considered for our indicator. There is a remarkable cross-country heterogeneity in this indicator.

Figure 2.9
Empirical distribution of the NSFR



Note: NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). Please see Appendix for further details.

Figure 2.10
Empirical distribution of the NSFR - by year



Note: NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). Please see Appendix for further details.

All in all, the analysis of these complementary liquidity indicators shows that there is a considerable heterogeneity in liquidity indicators both across countries and over time. Before the crisis, the loan-to-deposit ratio, the interbank ratio and the NSFR showed some deterioration. In turn, the liquidity ratio decreased after the crisis started, with a marked growth of customer deposits and short-term funding (while liquid assets recorded only a mild increase). Hence, even though most banks did not have to sell liquid assets to face short term funding needs, their maturity profile took a pronounced turn for the worse. During this period, many banks were not able to issue medium and long-term debt securities, thus shortening the average maturity of their liabilities. Nevertheless, liquidity creation does not seem to have been affected by these developments. Despite evident balance sheet adjustments, banks worldwide continued to perform their vital intermediation function.

In the next section we will provide some insight on which factors are relevant to explain the heterogeneity in liquidity indicators.

2.4 How do banks manage liquidity risk?

Even though liquidity risk management is one of the most important decisions in the prudent management of financial institutions, there is scarce empirical evidence on the determinants of liquidity indicators. Using our dataset, we are able to explore which bank characteristics may be relevant in explaining liquidity indicators. In Table 2.3 we present some results on the five liquidity indicators described in the previous section: i) loans to customer deposits (column 1); ii) the interbank ratio (column 2); iii) the liquidity ratio (column 3); iv) liquidity creation (column 4); and v) net stable funding ratio (column 5). All specifications use robust standard errors, bank fixed-effects and country-year fixed effects, such that:

$$Liqx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 Capital_{it-1} + \beta_2 Banksize_{it} + \beta_3 Profitability_{it-1} +$$

$$+\beta_4 Cost\_inc_{it-1} + \beta_5 Lend\_spec_{it-1} + \beta_6(Liq - x_{it-1}) + i_t + \varepsilon_{it} \qquad (2.1)$$

where $Liqx_{it}$ is the liquidity indicator analyzed, α_0 is a constant, α_i is the bank fixed effect, α_{nt} is the country-year fixed effect, i_t is the year fixed effect and ε_{it} is the estimation residual. Bank fixed effects allow to control for all time-invariant bank characteristics, while country-year fixed effects control for all country-specific time-varying shocks, such as changes in macroeconomic and financial conditions, or changes in the regulatory environment. By controlling also for time fixed-effects, we are able to orthogonalize all systematic and common shocks to banks. As explanatory variables, we use a set of core bank indicators on solvency, size, profitability, efficiency and specialization. $Capital_{it}$ is the total capital ratio calculated according to the rules defined by the Basel Committee. $Banksize_{it}$ is measured by the log of Assets and $profitability_{it}$ includes the return on assets and the net interest margin. $Cost\_inc_{it}$ refers to the cost-to-income ratio, which is a proxy for cost-efficiency, and $lend\_spec_{it}$ measures to what extent a bank is specialized in lending, by considering net loans as a percentage of total assets. Finally, $(Liq - x_{it})$ refers to the other liquidity indicators, i.e., $x_{it} \neq -x_{it}$ (the only exception is the interbank ratio, which is never included as an explanatory variable, given that it would imply a considerable reduction in the sample size). All variables are lagged by one period to mitigate concerns of simultaneity and reverse causality.

Table 2.3 - Determinants of liquidity indicators

Dependent variable:	**Loan to deposits**		**Interbank ratio**		**Liquidity ratio**		**Liquidity creation**		**NSFR**	
	(1)		(2)		(3)		(4)		(5)	
Total capital ratio $_{t-1}$	0.19		-0.46		0.08		-0.14		0.07	
	1.01		*-0.46*		*1.15*		*-1.56*		*0.85*	
Log Assets $_{t}$	5.09	**	-8.05		-2.50	**	-5.87	***	-2.69	**
	2.09		*-0.46*		*-2.23*		*-4.96*		*-2.46*	
Net interest margin $_{t-1}$	-1.82	**	3.35		-0.05		-1.37	***	2.11	***
	-2.29		*0.78*		*-0.17*		*-3.96*		*5.95*	
Return on assets $_{t-1}$	1.42	*	-1.51		-0.63	**	0.68	*	-1.43	***
	1.73		*-0.25*		*-2.11*		*1.81*		*-3.66*	
Cost-to-income $_{t-1}$	0.02		-0.13		0.00		0.08	***	-0.04	**
	0.43		*-0.54*		*-0.04*		*3.72*		*-2.10*	
Net loans to total assets $_{t-1}$	1.04	***	-2.24	**	-0.20	***	0.29	***	0.11	**
	8.79		*-2.24*		*-5.51*		*6.72*		*2.03*	
Loans to customer deposits $_{t-1}$	-		0.16		0.00		-0.02	**	-0.08	***
	-		*1.31*		*-0.39*		*-2.01*		*-5.77*	
Interbank ratio $_{t-1}$	-		-		-		-		-	
	-		-		-		-		-	
Liquidity ratio $_{t-1}$	0.30	***	0.02		-		0.23	***	0.04	
	3.54		*0.05*		-		*7.90*		*1.36*	
Liquidity creation $_{t-1}$	-0.49	***	1.59	***	0.11	***	-		-0.14	***
	-5.13		*3.21*		*3.63*		-		*-4.22*	
NSFR $_{t-1}$	-0.61	***	1.30	***	0.17	***	-0.15	***	-	
	-7.38		*2.73*		*6.16*		*-5.31*		-	
D2004	1.67	**	0.48		-0.34		-3.74	***	2.10	***
	2.18		*0.03*		*-0.93*		*-10.36*		*5.36*	
D2005	2.27	**	6.28		-0.53		-3.66	***	1.13	**
	2.26		*0.43*		*-1.49*		*-8.58*		*2.55*	
D2006	3.64	***	9.37		0.36		-7.35	***	4.49	***
	4.44		*0.72*		*1.15*		*-21.51*		*11.57*	
D2007	5.56	***	-0.93		-0.02		-9.08	***	4.79	***
	6.58		*-0.08*		*-0.07*		*-23.22*		*12.18*	
D2008	7.50	***	-6.93		-1.38	***	-11.59	***	5.08	***
	10.76		*-0.80*		*-5.37*		*-27.44*		*13.43*	
Constant	348.9	***	445.2		-19.8		-593.2	***	355.24	***
	4.82		*0.66*		*-0.63*		*-15.33*		*9.92*	
Number of observations	7,018		1,885		7,018		7,020		7,020	
Number of banks	1,735		529		1,736		1,738		1,738	
R2 within	0.160		0.059		0.102		0.366		0.160	
R2 between	0.151		0.038		0.303		0.139		0.165	
R2 overall	0.129		0.017		0.276		0.103		0.138	
Frac. of variance due to bank FE	0.965		0.729		0.966		0.998		0.984	

Notes: All regressions include country-year fixed-effects, bank fixed-effects and robust standard errors. t-statistics in italics. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions. The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. All these variables are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

On average, when banks become larger, they seem to become generally riskier in what concerns liquidity risk management, showing higher loan-to-deposit ratios, weaker interbank positions, smaller liquidity buffers and less stable funding structures. However, larger banks seem to create less liquidity, as a percentage of total assets, thus being less exposed in this risk dimension.

Even though some relationship between capital and liquidity could be expected (Berger and Bouwman, 2009, Diamond and Rajan, 2000, 2001a), the total capital ratio is not statistically significant in any of the specifications tested.

The relationship between profitability and liquidity risk is rather mixed. On the one hand, when banks obtain larger net interest margins, they seem to display lower liquidity risk (measured by loan to deposits, liquidity creation and NSFR). On the other hand, when banks record higher overall profitability, as measured by return on assets, they show more liquidity risk (higher loan to deposit ratios, more liquidity creation, lower liquidity buffers and less stable funding structures). Banks that are more profitable in their basic intermediation function seem to have less risky funding structures, while banks that are broadly more profitable (possibly obtaining larger gains from other income sources) tend to be riskier in their liquidity risk management. These are possibly banks that adopt riskier strategies in order to boost profitability, thus being more vulnerable to funding liquidity risk. This result is in line with Demirgüç-Kunt and Huizinga (2010), who show that banks that rely on strategies based on non-interest income and on short-term funding are significantly riskier.

In turn, when banks become more efficient, with lower cost-to-income ratios, they create, on average, less liquidity and have larger net stable funding ratios. Finally, one of the most relevant variables in explaining liquidity ratios is bank specialization, measured as net loans as a percentage of total assets: banks that become more specialized in lending to customers tend to have, as would be expected, higher loan to deposit ratios and create more liquidity. These banks also display lower interbank ratios (i.e., they are more likely net borrowers) and lower liquidity ratios. Hence, even though banks that concentrate most of their assets in lending are usually perceived as having a more traditional, and perhaps more stable, intermediation profile, these are the banks that tend to show worse liquidity ratios (the only exception is the result obtained for the NSFR, which goes in the opposite direction). Hence, even though these banks are usually deemed as globally less prone to risk-taking, they tend to show larger funding gaps and maturity mismatches.

The coefficients on liquidity indicators show that these capture different dimensions of liquidity risk. Indeed, with the exception with the coefficients associated with the NSFR, the signals of these coefficients are contrary to what could be expected ex-ante. This confirms the need to simultaneously assess these different dimensions of liquidity risk.

Finally, it is relevant to note that a large part of the variation in liquidity ratios cannot be attributable to the observed financial ratios analyzed. Indeed, as shown in the table, bank fixed effects account for a very large fraction of the variance. This result is entirely consistent with evidence obtained by Gropp and Heider (2010) regarding the determinants of banks' capital ratios. These authors find that unobserved time invariant bank fixed effects are ultimately the most important determinant of banks' capital ratios.

In sum, when banks become larger and more profitable, they tend to exhibit, on average, more liquidity risk, most notably if they have a more traditional intermediation profile, focusing on lending to customers. Given that liquidity risk can be associated with maturity transformation (i.e., with the main role of banks in an economy), this may imply that the banks that take more risk in liquidity are usually those better equipped to do so, as they should be better able to withstand adverse shocks. In turn, banks with larger net interest margins and with better cost-efficiency ratios seem to be generally less risky in their liquidity management. Finally, there does not seem to exist an empirical relationship between capital and liquidity, thus suggesting that these two dimensions should be regulated through different instruments.

2.5 Are other banks' decisions relevant?

In the previous section we shed some light on the role of different bank characteristics on their observed liquidity strategies. However, it is possible to argue that banks do not optimize their liquidity choices strictly individually, and may take into account other banks' choices. In fact, when banks believe that they may be bailed out in case of severe financial distress (for being too-big, too-systemic or too-interconnected to fail), they may actually have incentives to herd, engaging in similar risk-taking and management strategies. For instance, Goodhart and Schoenmaker (1995) show that banks are more often rescued than liquidated in case of distress. Against this background, when other banks are taking more risk, a specific bank may have the incentives to engage in similar strategies. These collective risk-taking strategies may be optimal from an individual perspective as they should allow banks to increase profitability without increasing the likelihood of bankruptcy, due to the explicit or implicit commitment of the lender of last resort, as theoretically conjectured by Ratnovski (2009).

In this section, we try to find evidence of possible herding behavior of banks in liquidity risk management, especially in the years before the global financial crisis. We begin by analyzing a herding measure that may provide some insight on this issue, in section 2.5.1. However, the identification and measurement of peer effects on individual choices is a challenging econometric problem, as discussed by Manski (1993). In section 2.5.2 we briefly discuss these identification problems and in section 2.5.3 we propose an empirical strategy to address these concerns and present our results.

2.5.1 A traditional measure of bank herd behavior

A possible way to examine if banks take into account each others' decisions in liquidity risk choices is to estimate measures of herding frequently used in financial markets (see, for example, Graham, 1999, Grinblatt et al, 1995, Scharfstein and Stein, 1990, or Wermers, 1999). To do that, we adapt the often used herding measure proposed by Lakonishok et al (1992) and applied to bank herding by Uchida and Nakagawa (2007) and, more recently, by Van den End and Tabbae (2012). This methodology allows testing the extent to which the liquidity choices of banks collectively deviate from what could be suggested by overall macroeconomic conditions. Implicitly, we are considering a concept of "rational herding", as defined by Devenow and Welch (1996). In other words, we do not consider that banks simply mimic each other's behaviors, but rather that they do so because there are important externalities that affect the optimal decision making process.

We compute:

$$H_i = |P_{it} - P_t| - E\,|P_{it} - P_t|$$

where P_{it} is the proportion of banks that show an increase in risk for a given liquidity indicator in each country and in each year, computed as $\frac{X_i}{N_i}$. X_i is the number of banks that recorded a deterioration of a liquidity indicator in a country in a given year, and N_i is the total number of banks operating in each country and in each year. For the loan-to-deposit and liquidity creation ratios, X_i refers to the number of banks that showed an increase in these ratios, while for the other three liquidity indicators X_i refers to the number of banks that recorded a decrease in these indicators, i.e., an increase in risk. P_t is the mean of P_{it} in each year (i.e., it is the average across all countries in a given year). The difference between P_{it} and P_t measures to what extent liquidity indicators in one country and in one year deviate from the overall liquidity indicators in that year, i.e. from common factors. According to the methodology proposed by Lakonishok et al (1992), when banks independently increase or decrease liquidity indicators, i.e. not due to herding effects, P_{it} and P_t become closer and $|P_{it} - P_t| \rightarrow 0$. However, when several banks collectively deviate and increase or decrease their liquidity indicators, P_{it} departs from P_t. In other words, when there is no herding, it can be assumed that some banks will increase risk, while others will simultaneously decrease risk, thereby leading to a smaller difference between P_{it} and P_t.

The second term in the equation is used to normalize the herding measure. If there is no herding, the expected value of the first term is positive, as discussed above. As such, the second term is subtracted to make the mean of H_i equal to zero under the null hypothesis of no herding.

Computing this measure at the country level is crucial if we consider that the incentives for herding are much stronger amongst national peers. The common belief of bailout is more likely to be shared by banks in the same country. Indeed, the arguments to support that banks take riskier strategies because banks operating in other countries do so are much weaker than when considered at the national level. This will be particularly true if competition between banks exists within markets segmented by national borders.

Table 2.4 shows our estimates for this herding measure for the five liquidity indicators. The estimates presented are the annual averages of H_i for each liquidity indicator, when $P_{it} > P_t$, i.e. when in a given country more banks are increasing risk than the average in all the other countries taken together. The larger the absolute value of H_i is, the stronger are herding behaviors (the sign of H_i cannot be interpreted as "positive" or "negative" herding, as it is affected by the normalization term).

The evidence supporting herd behavior based on this indicator is statistically very strong for all the indicators. The only exception is the interbank ratio. This can be explained by the fact that interbank market positions close, i.e., net lending positions of some banks should be offset by net borrowing positions of other banks. For all the other indicators, the results are remarkably strong, thus supporting the hypothesis of collective risk taking before the crisis[17].

[17] When there are few banks in a given country, the results might be more volatile. For robustness purposes, we ran the estimations excluding all countries with less than 100 observations. The results are not meaningfully affected by this change.

Table 2.4 - Measurement of herd behavior (mean)

	Loans to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
2003	0.124 ***	0.035 **	-0.037 ***	0.130 ***	0.117 **
2004	-0.040 ***	0.009	-0.030 ***	-0.033 ***	-0.034 ***
2005	0.137 ***	0.009	0.133 ***	-0.030 ***	-0.041 ***
2006	0.112 ***	-0.007	-0.028 ***	-0.031 ***	-0.023 ***
2007	-0.012 ***	0.009 *	0.049 ***	0.035 ***	-0.024 ***
2008	0.111 ***	-0.016 ***	0.139 ***	0.057 ***	0.074 ***
2009	0.188 ***	0.032 ***	0.150 ***	0.093 ***	0.070 ***

Notes: Herd behavior measure based on Uchida and Nakagawa (2007) and Lakonishok et al (1992). The herding measure is computed as Hi = |Pit - Pt | - E|Pit - Pt |, where Pit is the proportion of banks that show an increase in risk for a given liquidity indicator in each country and in each year (i.e., increases in the loan to deposit ratio and liquidity creation or decreases in the interbank ratio, liquidity ratio or NSFR) and Pt is the mean of Pit in each year. Liquidity indicators as defined in previous tables. In each cell are reported the annual averages of Hi for each liquidity indicator, when Pit>Pt, i.e. when in a given country more banks are increasing risk than the average in all the other countries taken together. The larger the absolute value of Hi is, the stronger are herding behaviors.*** significant at 1%; ** significant at 5%; * significant at 10%, based on a t-test.

Nevertheless, this traditional herding measure has several limitations and cannot be regarded as a full characterization of collective risk taking. This is essentially a static measure and, more importantly, it only considers whether or not there was an increase in risk, without considering its magnitude. Furthermore, this measure does not take into account all other possible determinants of liquidity choices. It is possible that common behaviors are observed because banks are affected by common shocks or because they share common characteristics, rather than by true herding behavior. Hence, only in a multivariate setting, where bank specific characteristics and time effects are explicitly controlled for, it becomes possible to isolate the impact of other banks' choices on each individual bank. In the next subsection we deal with the identification challenges raised by this multivariate analysis.

2.5.2 The reflection problem and identification strategies

In a multivariate setting, the impact of peers' liquidity indicators on a bank's liquidity decisions could be estimated through the following adapted version of equation 1:

$$Liqx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} +$$

$$+\beta_3 profitability_{it-1} + \beta_4 Cost\_inc_{it-1} + \beta_5 lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it} \tag{2.2}$$

where $\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it}-1}$ represents the average liquidity indicators of peers and all the other variables and parameters are defined as in equation 1. In this setting, the coefficient β_0 captures the extent to which banks' liquidity choices reflect those of the relevant peer group. We recall that we are controlling for bank, time and country-year fixed effects.

However, this estimation entails some econometric problems: as we argue that peer choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers. This reverse causality problem in peer effects is usually referred to as the reflection problem. This problem was initially described by Manski (1993), who distinguishes three different dimensions of peer effects: i) exogenous or contextual effects, related to the influence of exogenous peer characteristics; ii) endogenous effects, arising from the influence of peer outcomes (in our case, peers' liquidity choices); and iii) correlated effects, which affect simultaneously all elements of a peer group. Empirically, it is very challenging to disentangle these effects. More specifically, Manski (1993) discusses the difficulties arising from the distinction between effective peer effects (either endogenous or exogenous) from other correlated effects. Furthermore, the identification of endogenous and exogenous effects is undermined by this reflection problem, as the simultaneity in peers' decisions should result in a perfect collinearity between the expected mean outcome of the group and its mean characteristics, as discussed also by Bramoullé et al (2009) and Carrell et al (2009).

This discussion makes clear that the estimation of equation 2 may not allow for the accurate estimation of peer effects. Our solution to this important identification problem relies on the use of an instrument to address this endogeneity problem. Manski (2000) argues that the reflection problem can be solved if there is an instrumental variable that directly affects the outcomes of some, but not all, members of the peer group[18]. As discussed in Leary and Roberts (2013) and Brown et al (2008), such an instrument must be orthogonal to systematic or herding effects. Given this, we use the predicted values of liquidity indicators of peer banks based on the regressions of the determinants of liquidity indicators presented in Table 2.3. The predicted values depend on the characteristics of the banks in the peer group, excluding bank i. These predicted values depend only on observable bank characteristics and should thus be orthogonal to systematic or herding effects. In other words, the predicted value of the liquidity indicators of peer banks should not directly affect $Liqx_{it}$, the liquidity indicator of bank i at time t, as these predicted values are based solely on observable bank characteristics. As we control also for time effects, we are able to orthogonalize all systematic shocks to banks. In addition, we also control for country-year fixed effects, in order to consider the effect of

[18]Other solutions to the reflection problem found in the literature are, for example, having randomly assigned peer groups (Sacerdote, 2001), variations in group sizes (Lee, 2007) or identifying social networks using spatial econometrics techniques (Bramoullé et al, 2009). Given the characteristics of peer groups in our sample, none of these solutions can be applied in our setting.

time-varying country characteristics that may simultaneously affect all banks in a given country. Furthermore, the predicted values of peer banks should be highly correlated with the average of the observed liquidity indicators, our potentially endogenous variable[19].

Formally, our instrumental variables approach is equivalent to the estimation of

$$Liqx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_0 \sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} + \beta_3 profit._{it-1} +$$

$$+\beta_4 cost\_inc_{it-1} + \beta_5 lend\_spec_{it-1} + \beta_6 (Liq - x_{it-1}) + i_t + \varepsilon_{it} \qquad (2.3)$$

where the first step equation is

$$\sum_{j \neq i} \frac{Liqx_{jt}}{N_{it} - 1} = \alpha_0 + \alpha_j + \alpha_{nt} + \gamma_1 \sum_{j \neq i} \frac{Liq\_predx_{jt}}{N_{it} - 1} + \beta_1 capital_{jt-1} + \beta_2 banksize_{jt} +$$

$$+\beta_3 prof._{jt-1} + \beta_4 cost\_inc_{jt-1} + \beta_5 lend\_spec_{jt-1} + \beta_6 (Liq - x_{jt-1}) + i_t + \varepsilon_{it}$$

[19] For a related solution to the identification of peer effects using instrumental variables, see Leary and Roberts (2013).

with $\sum\limits_{j\neq i}\frac{Liq_predx_{jt}}{N_{it}-1}$representing the average predicted values for $Liqx_{it}$ for the peer group in the equation:

$$Liq\_predx_{it} = \alpha_0 + \alpha_i + \alpha_{nt} + \beta_1 capital_{it-1} + \beta_2 banksize_{it} + \beta_3 prof._{it-1}+$$

$$+\beta_4 cost\_inc_{it-1} + \beta_5 lend\_spec_{it-1} + \beta_6(Liq - x_{it-1}) + i_t$$

Using this specification, we are able to identify peer effects, after adequately having dealt with the reflection problem. As before, we define the benchmark peer group as the banks operating in the same country and in the same year. These are the banks that are more likely to engage in collective risk-taking behaviors due to implicit or explicit bailout expectations. Let us suppose that in a given country several banks engage in funding liquidity strategies that are deemed as globally risky (e.g., excessive reliance in short term debt to finance long-term assets, large funding gaps or persistent tapping of interbank markets). If several banks engage in these strategies simultaneously, there is naturally an increase in systemic risk. As discussed by Rochet and Tirole (1996) and Ratnovski (2009), a lender of last resort is not necessarily going to bailout one bank that gets into trouble because of its own idiosyncratic wrong choices (unless this bank is clearly too big or too systemic to fail). However, if several banks are at risk, the lender of last resort needs to take the necessary actions to contain systemic risk. In this case, the likelihood of a bailout should increase, as if one of these banks gets into trouble, very likely other banks will follow very soon, thus becoming too-many-to-fail (Acharya and Yorulmazer, 2007). Given this incentive structure, a given bank in that country has clearly high incentives to engage in similar risky but profitable strategies. However, the same cannot be said for a bank operating in another country, where there is a different lender of last resort. This reasoning justifies our choice for the reference peer group. Nevertheless, we will later relax this hypothesis and test other possible peer groups.

2.5.3 Empirical results

In Table 2.5 we present the results of the instrumental variable approach in the estimation of peer effects in liquidity risk management.

In the first five columns we present the results of the estimation of equation 2. Hence, in these columns the peer effects are included in the regressions without properly addressing the reflection problem discussed before. When running this simple, yet possibly biased, estimation, we find strong evidence of positive peer or herding effects in individual banks' choices for all liquidity indicators. The riskier are the funding and liquidity strategies of other banks in a given country, the riskier will tend to be the choices of each bank individually. However, as discussed above, these preliminary estimates may not be dealing adequately with the endogeneity problem underlying the estimation of peer effects.

Table 2.5 - Regressions on peer effects in liquidity strategies

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios) Second-step regressions					First-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Peer effects	0.32***	0.19**	0.46***	0.81***	0.43***	0.39***	0.81	0.72***	0.56***	0.36	1.13***	0.35***	0.86***	0.92***	0.24***
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*6.64*	*1.09*	*8.88*	*9.02*	*1.08*	*32.47*	*3.24*	*29.16*	*31.28*	*7.21*
Total capital ratio $_{t-1}$	0.19	-0.60	0.03	-0.19**	0.08	0.18*	-0.87	0.01	-0.18***	0.08	0.12**	0.57	0.05***	0.03	-0.02
	1.01	*-0.61*	*0.46*	*-2.29*	*0.91*	*1.75*	*-0.78*	*0.15*	*-3.63*	*1.51*	*2.20*	*1.36*	*3.07*	*1.15*	*-0.83*
Log Assets $_{t}$	2.76	-6.20	-1.46	-1.73	-2.86**	2.19*	-3.24	-0.88*	-3.02***	-2.80***	0.51	-4.98	-0.41**	-2.86***	0.87***
	1.12	*-0.35*	*-1.23*	*-1.61*	*-2.56*	*1.77*	*-0.23*	*-1.82*	*-4.95*	*-4.77*	*0.79*	*-0.91*	*-2.05*	*-10.22*	*3.47*
Net interest margin $_{t-1}$	-1.42*	3.17	-0.03	-1.08***	1.90***	-1.32***	2.72	-0.02	-1.17***	1.94***	-0.53**	0.60	-0.15**	-0.29***	0.41***
	-1.88	*0.74*	*-0.10*	*-3.26*	*5.28*	*-2.92*	*0.71*	*-0.10*	*-5.71*	*7.18*	*-2.26*	*0.38*	*-2.05*	*-2.76*	*4.39*
Return on assets $_{t-1}$	1.39*	-0.70	-0.62**	0.56	-1.34***	1.36***	0.99	-0.62***	0.60***	-1.36***	0.60**	-4.16**	-0.16*	-0.05	-0.19*
	1.78	*-0.12*	*-2.25*	*1.59*	*-3.46*	*2.69*	*0.18*	*-3.18*	*2.60*	*-5.25*	*2.25*	*-2.07*	*-1.88*	*-0.39*	*-1.85*
Cost-to-income $_{t-1}$	0.02	-0.11	0.00	0.05***	-0.04*	0.02	-0.11	-0.01	0.06***	-0.04***	0.03**	-0.12	-0.01	0.02***	-0.02***
	0.56	*-0.45*	*-0.22*	*2.64*	*-1.81*	*0.90*	*-0.36*	*-0.55*	*4.43*	*-2.80*	*2.28*	*-0.97*	*-1.31*	*2.79*	*-2.93*
Net loans to tot assets $_{t-1}$	0.95***	-2.15**	-0.16***	0.26***	0.12**	0.93***	-1.67*	-0.13***	0.26***	0.12***	0.11***	-0.49	-0.05***	0.04**	-0.01
	8.45	*-2.15*	*-4.46*	*6.34*	*2.18*	*15.20*	*-1.88*	*-5.39*	*9.17*	*3.72*	*3.37*	*-1.62*	*-5.37*	*2.54*	*-0.99*
Loans to cust deposits $_{t-1}$	-	0.15	0.00	0.00	-0.08***	-	0.10	0.00	0.00	-0.08***	-	0.05	0.00	-0.02***	0.00
	-	*1.24*	*-0.30*	*0.43*	*-6.02*	-	*0.74*	*-0.49*	*-0.51*	*-10.95*	-	*1.01*	*1.03*	*-6.33*	*0.63*
Interbank ratio $_{t-1}$	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Liquidity ratio $_{t-1}$	0.31***	-0.05	-	0.12***	0.05*	0.32***	-0.20	-	0.15***	0.05**	-0.02	0.23	-	0.12***	-0.04***
	3.81	*-0.15*	-	*4.34*	*1.90*	*7.47*	*-0.46*	-	*6.72*	*2.22*	*-1.07*	*1.36*	-	*11.05*	*-4.50*
Liquidity creation $_{t-1}$	-0.40***	1.54***	0.06**	-	-0.13***	-0.38***	1.41***	0.03	-	-0.13***	-0.09***	0.11	0.06***	-	-0.04***
	-4.31	*3.17*	*1.98*	-	*-3.79*	*-7.78*	*3.29*	*1.49*	-	*-5.92*	*-3.68*	*0.65*	*7.54*	-	*-4.65*
NSFR $_{t-1}$	-0.55***	1.26***	0.13***	-0.12***	-	-0.54***	1.12***	0.11***	-0.13***	-	-0.11***	0.14	0.05***	-0.03***	-
	-7.11	*2.70*	*5.11*	*-4.53*	-	*-13.66*	*2.68*	*7.05*	*-7.58*	-	*-5.42*	*0.87*	*7.21*	*-3.84*	-
Constant	357.8***	288.2	-26.7	69.7	72.8	361.5***	-473.7	-30.1	-137.2**	119.3	-303.9***	382.2	39.7***	-100.9***	587.8***
	4.95	*0.41*	*-0.86*	*1.27*	*1.31*	*6.83*	*-0.56*	*-1.48*	*-2.44*	*0.54*	*-10.48*	*1.40*	*4.59*	*-3.84*	*39.78*
Number of observations	7,016	1,882	7,016	7,019	7,019	7,010	1,877	7,010	7,012	7,012	7,010	1,877	7,010	7,012	7,012
Number of banks	1,734	528	1,735	1,737	1,737	1,733	527	1,734	1,736	1,736	1,733	527	1,734	1,736	1,736
R2 within	0.187	0.066	0.141	0.477	0.186	0.186	0.009	0.127	0.467	0.186	0.427	0.135	0.324	0.705	0.484
R2 between	0.155	0.079	0.135	0.329	0.501	0.158	0.003	0.000	0.095	0.524	0.330	0.041	0.573	0.399	0.555
R2 overall	0.132	0.051	0.105	0.331	0.455	0.134	0.013	0.001	0.055	0.471	0.316	0.036	0.466	0.313	0.494

Notes: All regressions include year, country-year and bank fixed-effects. t-statistics in italics. Peers are defined as the j?i banks operating in the same country and in the same year as bank i. Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions (one for each liquidity indicator), where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 2.3. Columns 11-15 show the first stage estimation results for these three instrumental variables regressions. The total capital ratio is calculated according to the regulatory rules defined by the Basel Committee. Net interest margin is defined as net interest income as a percentage of earning assets. Return on assets computed as net income as a percentage of average assets. The cost-to-income ratio is computed as banks operational costs (overheads) as a percentage of income generated before provisions.
The interbank ratio is defined as interbank assets as a percentage of interbank liabilities (loans to other banks as a percentage of loans from other banks). The liquidity ratio is defined as liquid assets (deposits and loans to banks with less than 3 months residual maturity, quoted/listed government bonds realizable within 3 months, cash and equivalent), as a percentage of customer deposits and short term funding. All these variables are included in the Bankscope database. Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding as a percentage of the required stable funding (i.e., assests that need to be funded). These last two variables are defined in detail in the Appendix. *** significant at 1%; ** significant at 5%; * significant at 10%.

The second group of columns (6-10) displays our main empirical results, when adequately dealing with the endogeneity problem created by considering peer effects. When we use the predicted values of peer's liquidity indicators as instruments, we conclude that the results presented in the first columns do not hold for all specifications: peer effects are not statistically significant for the interbank ratio and NSFR. For the other indicators, peer effects continue to be strongly statistically significant and vary between 0.39 (for the loan to deposit ratio) and 0.72 (for the liquidity ratio). The different results obtained when the endogeneity problem is addressed are an indication that neglecting endogeneity in peer effects may originate biased and incorrect results.

As discussed before, a good instrument should have an important contribution in explaining the potentially endogenous variable, i.e. the average peers' liquidity choices, but it should not directly affect that the dependent variable. In the previous sub-section we discussed why the latter condition holds in our setting, whereas in the last group of columns of Table 2.5 we show that the chosen instrument is strongly statistically significant in all the regressions.

To better understand how these peer effects work and to ensure that the results are consistent under a wide set of specifications, we run a large battery of robustness tests.

In Table 2.6 we present some of the most relevant tests conducted. All the estimations were performed without and with instrumental variables, in columns (1)-(5) and (6)-(10), respectively. First step regressions are reported in columns (11)-(15).

Table 2.6 - Regressions on peer effects in liquidity strategies - robustness

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - (IV = pred. values of rivals' liquidity ratios) Second-step regressions					First-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Baseline															
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.81	0.72 ***	0.56 ***	0.36	1.13 ***	0.35 ***	0.86 ***	0.92 ***	0.24 ***
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*6.64*	*1.09*	*8.88*	*9.02*	*1.08*	*32.47*	*3.24*	*29.16*	*31.28*	*7.21*
Before the crisis															
Peer effects	0.04	0.06	0.31 ***	0.46 ***	0.12	0.33	1.36	0.76 **	0.35 ***	0.33 *	0.48 ***	-0.15	0.33 **	0.57 ***	-0.63 ***
	0.50	*0.51*	*2.86*	*5.24*	*1.54*	*1.44*	*0.37*	*2.32*	*2.74*	*1.94*	*8.04*	*-0.74*	*2.32*	*16.12*	*-15.89*
Removing banks with asset growth above 50%															
Peer effects	0.32 ***	0.16 *	0.42 ***	0.79 ***	0.39 ***	0.42 ***	0.21	0.64 ***	0.53 ***	0.42 ***	0.87 ***	0.17	0.84 ***	0.70 ***	0.53 ***
	4.50	*1.83*	*6.99*	*17.94*	*7.00*	*6.06*	*0.13*	*7.98*	*7.97*	*2.60*	*27.29*	*1.43*	*29.51*	*27.98*	*14.46*
Excluding US banks															
Peer effects	0.26 ***	0.18 **	0.25 ***	0.24 ***	0.19 ***	0.22 **	0.80	0.42 **	-1.87	0.28 *	1.07 ***	0.29 ***	0.77 ***	0.18 **	0.73 ***
	4.16	*2.15*	*4.24*	*2.92*	*2.94*	*2.22*	*0.92*	*2.43*	*-1.47*	*1.95*	*16.23*	*2.76*	*12.86*	*2.51*	*14.31*
Exclude smaller countries (less than 50 observations)															
Peer effects	0.37 ***	0.18	0.52 ***	0.84 ***	0.46 ***	0.48 ***	0.12	0.69 ***	0.56 ***	0.25	1.22 ***	0.59 ***	0.97 ***	1.14 ***	0.39 ***
	5.33	*1.64*	*7.62*	*18.78*	*7.06*	*8.37*	*0.24*	*8.66*	*10.60*	*1.06*	*38.73*	*5.40*	*32.91*	*38.84*	*10.67*
Western Europe banks															
Peer effects	-0.01	0.15	0.00	0.24 **	0.19 ***	0.24	-0.71	-1.95	-10.43	0.24	1.02 ***	-0.14 ***	-0.05 **	-0.02	-0.10 ***
	-0.12	*1.61*	*0.00*	*2.45*	*2.79*	*1.03*	*-0.77*	*-1.20*	*-0.42*	*0.43*	*8.06*	*-2.64*	*-1.97*	*-0.44*	*-3.31*
Eastern Europe banks															
Peer effects	0.42 ***	0.14	0.40 ***	0.20	0.13	0.35 ***	1.05	1.09 **	0.28	0.25 *	1.30 ***	-0.08	0.37 ***	0.22 **	1.11 ***
	5.24	*1.17*	*4.26*	*1.59*	*1.22*	*2.98*	*0.26*	*2.22*	*0.26*	*1.73*	*13.89*	*-0.61*	*4.62*	*2.15*	*17.58*
US, Canada and Western Europe banks															
Peer effects	0.02	0.22 **	0.38 ***	0.79 ***	0.43 ***	0.05	-0.47	10.01	0.63 ***	0.23	1.62 ***	-0.17 **	0.04	1.85 ***	-0.49 ***
	0.30	*2.47*	*4.41*	*13.12*	*6.60*	*0.57*	*-0.48*	*0.89*	*8.78*	*1.47*	*25.47*	*-2.42*	*0.89*	*32.36*	*-18.32*
Excluding countries more directly affected during the global crisis															
Peer effects	0.27 ***	0.19 **	0.28 ***	0.21 **	0.15 **	0.18 *	0.15	0.49 ***	-1.35	0.18	1.16 ***	0.39 ***	0.87 ***	0.26 ***	0.80 ***
	4.09	*2.09*	*4.36*	*2.41*	*2.06*	*1.80*	*0.21*	*2.86*	*-1.48*	*1.18*	*15.64*	*3.41*	*13.31*	*3.14*	*13.75*
Without country-year fixed effects															
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.33 **	0.81	0.72 ***	0.43 ***	0.36	0.18 ***	0.35 ***	0.86 ***	0.04 ***	0.24 ***
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*2.57*	*1.09*	*8.88*	*3.46*	*1.08*	*13.68*	*3.24*	*29.16*	*14.63*	*7.21*
With country and year fixed effects (random-effects estimation)															
Peer effects	0.24 ***	0.03	0.37 ***	0.78 ***	0.37 ***	0.23 ***	-0.29	0.33 ***	0.46 ***	0.02	1.08 ***	0.34 ***	1.23 ***	1.12 ***	0.29 ***
	4.13	*0.41*	*6.82*	*19.34*	*6.95*	*4.72*	*-0.71*	*5.02*	*5.21*	*0.11*	*46.27*	*6.48*	*41.18*	*23.40*	*12.83*
Without liquidity controls															
Peer effects	0.36 ***	0.21 **	0.53 ***	0.81 ***	0.41 ***	0.54 ***	1.33 **	0.83 ***	0.54 ***	0.25	0.89 ***	0.49 ***	0.63 ***	1.02 ***	-0.18 ***
	5.33	*2.47*	*8.51*	*19.91*	*6.90*	*6.37*	*1.97*	*7.17*	*8.58*	*0.44*	*21.72*	*3.83*	*20.48*	*29.89*	*-4.38*
Controlling for leverage (instead of capital ratio)															
Peer effects	0.28 ***	0.16 ***	0.45 ***	0.76 ***	0.46 ***	0.36 ***	-0.11	0.59 ***	0.66 ***	0.23 ***	1.50 ***	0.77 ***	1.41 ***	1.89 ***	1.18 ***
	4.05	*2.73*	*8.95*	*21.44*	*9.97*	*8.46*	*-0.38*	*10.69*	*16.09*	*3.50*	*51.95*	*8.71*	*46.47*	*48.34*	*40.81*
Only after 2004															
Peer effects	0.41 ***	0.24 ***	0.49 ***	0.89 ***	0.53 ***	0.47 ***	1.04 *	0.77 ***	0.58 ***	0.45 **	1.15 ***	0.54 ***	0.84 ***	0.83 ***	0.48 ***
	6.18	*3.85*	*8.04*	*20.90*	*9.01*	*6.51*	*1.80*	*7.11*	*6.41*	*2.31*	*26.73*	*4.37*	*21.83*	*21.72*	*12.38*
Instrument: idiosyncratic equity returns (listed banks)															
Peer effects	0.34 **	0.59 ***	0.23 **	0.53 ***	0.48 ***	0.06	-0.92	2.04 **	1.28 *	0.59 **	-0.01 ***	0.00	0.00 **	0.00 ***	0.01 ***
	2.29	*4.94*	*2.32*	*4.31*	*5.31*	*0.40*	*-0.01*	*2.11*	*1.70*	*2.00*	*-7.78*	*-0.01*	*2.34*	*-3.71*	*9.52*
Peer effects using predicted values (without IV)															
Peer effects	0.44 ***	0.28	0.62 ***	0.51 ***	0.09	-	-	-	-	-	-	-	-	-	-
	6.57	*1.12*	*8.82*	*8.32*	*1.06*										
Accounting for predicted regressors with bootstrapped standard errors															
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.83	0.73 ***	0.56 ***	0.34	-	-	-	-	-
	4.48	*2.19*	*7.57*	*17.13*	*7.62*	*3.45*	*0.96*	*4.74*	*4.74*	*0.81*					

Notes: Peers are defined as the $j?i$ banks operating in the same country and in the same year as bank i. t-statistics in italics. Each line shows the coefficients for peer effects for different robustness tests. The pre-crisis period refers to the years 2002-2006. Countries considered as most directly affected by the global financial crisis include US, Iceland, Greece, Ireland, Portugal, Spain and Italy. Idiosyncratic equity returns computed as the difference between the banks annual total equity returns and the S&P Banks Index annual return. In the regressions with bootstrapped standard errors two year dummies had to be excluded. Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 2.3. Columns 11-15 show the first stage estimation results for these instrumental variables regressions.

All the regressions use the same control variables as those reported in Table 2.5. All regressions include year, country-year and bank fixed-effects, unless otherwise stated. *** significant at 1%; ** significant at 5%; * significant at 10%.

First, we exclude the crisis period, so as to focus the analysis on possible peer effects in the years before the global financial crisis. The peer effect coefficient for the loan to deposit ratio is not significant in this period, suggesting that collective risk taking behaviors before the crisis were apparent mainly in the liquidity ratio and in liquidity creation. In addition, the results for the NSFR are now marginally significant.

Second, we remove from the sample banks with year-on-year asset growth above 50%, as these banks may have been involved in mergers and acquisitions. Still, the results remain consistent.

US banks represent slightly less than one quarter of the sample. In order to ensure that the results are not influenced by this, we exclude all US banks from the sample. The results are globally consistent, though slightly less significant, both economically and statistically. The results also remain broadly consistent when we exclude smaller countries from the sample. In addition, we also estimate the regressions separately for Western and Eastern European banks, and for US, Canada and Western Europe banks together. The results are not statistically significant when only Western Europe banks are considered and are very weak for US, Canada and Western Europe banks. In turn, the results are stronger for banks from Eastern Europe, though still weaker than for the entire sample. One tentative explanation for this result might be the strong presence of foreign banks in these countries, which may be associated with stronger peer effects. Finally, we also exclude the countries more directly affected by the global financial crisis from the regressions. The results are broadly consistent, though slightly weaker.

For robustness purposes, we also run our estimates without using country-year fixed effects, with separate country and year fixed effects (using a random-effects estimation) and without controlling for liquidity indicators. In all cases, the results are robust, becoming slightly stronger in the last case.

In our baseline specification, we used the total capital ratio as an explanatory variable. However, the global financial crisis showed that, in many cases, the leverage ratio was better able to capture the financial situation of banks. To address this issue, we estimated the peer effect regressions using the leverage ratio (measured as equity over total assets) instead of the total capital ratio. The results are broadly consistent and somewhat stronger, as the peer effects on the NSFR become statistically significant. However, it should be noted that this change may be at least partly due to the larger number of observations used in this estimation, given that data on the total capital ratio is missing for many banks in the sample.

We also consider data only from 2004 onwards, in order to avoid using accounting information that is time inconsistent, given that in many countries common accounting reporting standards (IFRS) were introduced around this time. The results become generally stronger.

Finally, we test alternative ways to estimate peer effects. First, we consider an entirely different instrument, based on the identification strategy followed by Leary and Roberts (2013). To identify peer effects in corporate financial policy, these authors looked for an instrument that would not affect directly the financing decisions of a given firm, but that would influence those of the peer group of firms. An instrument that fulfills these exclusion and relevance conditions is the idiosyncratic component of peer firms' equity returns. We follow a similar approach, by computing bank-specific equity returns as the difference between the bank's returns and those of the S&P banks index in a given year[20]. Even though the sub-sample of listed banks used to compute this alternative estimation of peer effects is much smaller than the original (roughly one quarter), we are still able to obtain statistically significant peer effects for the liquidity ratio, for liquidity creation and for the NSFR.

Second, we consider an adapted version of our identification strategy, based on the social multiplier proposed by Sacerdote (2011) and Glaeser et al (2003). The basic idea is to use the peer group average of the predicted values arising from the regressions on liquidity determinants directly in the peer effects

[20] This approach is simpler than that used by Leary and Roberts (2013), who estimate idiosyncratic returns using an augmented factor model.

regressions (equation 1), instead of using them as instruments for the peer effects[21]. The results of this alternative estimation approach are remarkably close to the baseline specification.

A potentially relevant econometric issue is related with the use of predicted regressors in the estimations. To be sure that this is not affecting the results, we present, at the bottom of Table 2.6, the results using bootstrapped standard errors[22]. The results are generally consistent.

All in all, the robustness analysis points to consistent evidence of significant peer effects in liquidity risk decisions.

Alternative peer group definitions In Table 2.7 we explore a different type of robustness analysis, by testing alternative definitions of peer groups. Indeed, the definition of the peer group is a critical issue in the analysis of peer effects (Manski, 2000) and deserves further analysis. Even though we believe that defining peers as other banks in the same country is the most reasonable assumption, due to the common lender of last resort, this definition may be

[21] Our estimates of the social multiplier are an adaption because of the level of aggregation considered. As discussed by Glaeser et al (2003), several levels of aggregation may be considered in the estimations of the social multiplier. In our case, we use the coefficients from an individual level regression to predict aggregate level outcomes for the peer group of each bank. We then regress observed individual outcomes on these aggregate predicted values to obtain the social multiplier.

[22] The estimated coefficients display minor differences because it was necessary to exclude two year dummies from the estimations, in order to obtain the degrees of freedom necessary for the bootstrapping.

challenged.

Table 2.7 - Regressions on peer effects in liquidity strategies - robustness on peer group definition

	Bank peer effects - country year peer group (without IV)					Bank peer effects - country year peer group - Second-step regressions					First-step regressions				
	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR	Loan to deposits	Interbank ratio	Liquidity ratio	Liquidity creation	NSFR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Baseline															
Peer effects	0.32 ***	0.19 **	0.46 ***	0.81 ***	0.43 ***	0.39 ***	0.81	0.72 ***	0.56 ***	0.36	1.13 ***	0.35 ***	0.86 ***	0.92 ***	0.24 ***
	4.87	*2.33*	*7.96*	*18.62*	*7.54*	*6.64*	*1.09*	*8.88*	*9.02*	*1.08*	*32.47*	*3.24*	*29.16*	*31.28*	*7.21*
Lagged peers															
Peer effects	0.13 **	-0.09	0.32 ***	0.38 ***	0.03	0.38 ***	0.19	0.75 ***	0.74 ***	0.79	1.19 ***	0.34 **	0.64 ***	0.63 ***	0.09 ***
	2.47	*-1.20*	*5.18*	*5.83*	*0.65*	*5.78*	*0.23*	*5.76*	*6.00*	*0.67*	*28.06*	*2.47*	*5.76*	*29.18*	*2.63*
Peers as other banks (in other countries) in the same quartile															
Peer effects	0.11	-0.09	-0.04	0.82 ***	0.21 ***	0.08	2.01	0.22	0.30	-0.11	0.10 ***	-0.11 ***	-0.14 ***	0.02 ***	0.06 ***
	1.04	*-0.36*	*-0.45*	*9.50*	*3.59*	*0.43*	*1.56*	*1.02*	*1.22*	*-0.39*	*31.52*	*-6.27*	*-29.37*	*19.71*	*13.12*
Large banks (4th quartile in each country)															
Peer effects	0.22 ***	0.07	0.30 ***	0.40 ***	0.27 ***	0.36 ***	-0.05	0.39 ***	0.10	0.35 ***	1.49 ***	0.97 ***	1.51 ***	0.53 ***	1.40 ***
	3.37	*1.16*	*3.82*	*5.97*	*4.40*	*7.15*	*-0.27*	*5.05*	*0.33*	*5.05*	*29.00*	*7.08*	*23.10*	*6.03*	*27.97*
Large banks (4th quartile in the sample)															
Peer effects	0.19 ***	0.23 **	0.40 ***	0.30 ***	0.23 ***	0.30 ***	-0.04	0.34 ***	1.60 *	0.21 *	1.33 ***	0.47 ***	1.14 ***	-0.18 **	0.73 ***
	3.22	*2.29*	*6.24*	*4.83*	*4.12*	*4.16*	*-0.07*	*3.21*	*1.67*	*1.69*	*22.13*	*3.52*	*18.39*	*-2.21*	*13.61*
Only larger banks (3rd and 4th quartiles)															
Peer effects	0.26 ***	0.11	0.42 ***	0.63 ***	0.39 ***	0.34 ***	0.63 **	0.59 ***	0.59 ***	0.33 **	1.45 ***	0.88 ***	1.37 ***	1.24 ***	0.71 ***
	3.39	*1.24*	*7.46*	*10.45*	*7.38*	*6.49*	*2.26*	*8.46*	*6.64*	*2.46*	*35.78*	*6.54*	*29.27*	*21.26*	*16.48*
Only smaller banks (1st and 2nd quartiles)															
Peer effects	0.21 ***	0.10	0.21 ***	0.75 ***	0.34 ***	0.24 ***	1.50 *	0.51 ***	0.98 **	0.16	1.53 ***	0.25 ***	0.85 ***	0.14 ***	0.93 ***
	3.89	*1.07*	*3.71*	*12.19*	*4.14*	*3.71*	*1.69*	*3.74*	*1.98*	*1.50*	*21.67*	*2.82*	*13.95*	*3.41*	*18.05*
Only larger banks (top 5 in each country)															
Peer effects	0.04	0.07	0.21 **	0.15 *	0.17 **	0.31 **	-0.27	-0.09	-0.04	0.26	1.03 ***	0.46 *	0.84 ***	0.65 ***	0.70 ***
	0.75	*0.94*	*2.39*	*1.78*	*2.27*	*2.57*	*-0.40*	*-0.45*	*-0.12*	*1.27*	*9.13*	*1.82*	*5.76*	*3.93*	*6.80*
Only larger banks (banks classified as SIFIs)															
Peer effects	-0.69 ***	-0.20	0.70 ***	-0.03	0.21	-0.70 ***	0.16	0.71 **	-0.27	0.48	0.83 ***	1.63 ***	2.03 ***	0.75 ***	1.07 ***
	-2.98	*-1.35*	*3.38*	*-0.14*	*1.11*	*-2.61*	*0.63*	*2.21*	*-0.52*	*1.27*	*4.67*	*4.57*	*3.88*	*2.80*	*4.30*
Only larger banks (banks that belong to the Euribor panel)															
Peer effects	0.10	-0.16	-0.02	0.46 **	0.17 *	0.05	-0.19	0.13	-0.37	0.38 *	1.12 ***	0.91 ***	0.46 **	0.49	0.81 ***
	0.68	*-1.31*	*-0.08*	*2.55*	*1.70*	*0.26*	*-0.52*	*0.19*	*-0.38*	*1.87*	*6.21*	*3.27*	*2.27*	*1.41*	*6.73*
Exclude larger banks (top 5 in each country)															
Peer effects	0.30 ***	0.15	0.41 ***	0.76 ***	0.40 ***	0.33 ***	1.74	0.91 ***	0.58 ***	-0.55	1.13 ***	0.14	0.69 ***	0.95 ***	0.14 ***
	4.57	*1.25*	*5.98*	*14.15*	*6.40*	*4.14*	*1.01*	*8.13*	*9.01*	*-0.81*	*25.33*	*1.61*	*22.73*	*32.34*	*3.84*
Small banks following large banks (4th quartile)															
Peer effects	0.26 ***	0.21 **	0.26 ***	0.59 ***	-0.01	0.27 ***	0.11	0.60 ***	-0.41 **	-0.15 **	1.47 ***	0.77 ***	1.56 ***	0.79 ***	1.28 ***
	5.01	*2.10*	*4.44*	*7.41*	*-0.24*	*6.07*	*0.48*	*11.18*	*-2.35*	*-2.15*	*39.39*	*8.41*	*30.80*	*13.97*	*33.65*
Small banks following large banks (top 5)															
Peer effects	0.22 ***	0.09	0.17 ***	-0.84 ***	-0.30 ***	0.16 ***	0.00	0.67 ***	-1.38 ***	-0.27 ***	1.16 ***	0.55 ***	0.94 ***	0.48 ***	1.64 ***
	3.86	*1.28*	*4.47*	*-9.66*	*-7.13*	*3.59*	*0.00*	*10.40*	*-4.33*	*-5.71*	*46.14*	*3.94*	*23.56*	*10.94*	*44.99*
Small banks following large banks (SIFI list)															
Peer effects	0.10 *	0.16	0.32 ***	-0.47 ***	0.00	0.25 ***	0.71 **	1.02 ***	-1.84 ***	0.33 ***	0.97 ***	0.98 ***	0.77 ***	0.77 ***	1.36 ***
	1.95	*1.17*	*3.29*	*-5.82*	*-0.01*	*4.57*	*2.46*	*12.33*	*-14.06*	*3.42*	*40.88*	*9.27*	*27.66*	*31.15*	*33.97*
Small banks following large banks (Euribor panel)															
Peer effects	0.17 **	0.91 ***	0.31 ***	-0.21 ***	-0.03	0.26 ***	2.12 ***	1.03 ***	-0.86 ***	-0.30 ***	0.74 ***	0.76 ***	0.53 ***	1.18 ***	0.94 ***
	2.04	*2.89*	*3.36*	*-3.41*	*-0.51*	*4.37*	*3.58*	*14.41*	*-9.77*	*-4.92*	*58.86*	*10.55*	*50.14*	*38.85*	*60.01*
Euro area as one peer group															
Peer effects	0.37 ***	0.22 **	0.57 ***	0.85 ***	0.47 ***	0.30 ***	0.23	0.68 ***	1.29 ***	4.00	0.90 ***	0.26 **	1.03 ***	0.18 ***	0.02
	5.22	*2.25*	*8.77*	*18.87*	*7.49*	*4.61*	*0.22*	*9.96*	*10.47*	*0.68*	*30.62*	*2.40*	*40.44*	*15.39*	*0.74*
Countries with liquidity regulation															
Peer effects	0.23 ***	0.18 *	0.45 ***	0.78 ***	0.33 ***	0.44 ***	-4.05	0.86 ***	0.46 ***	0.37	1.02 ***	-0.06	0.71 ***	0.90 ***	-0.07 **
	2.91	*1.87*	*6.85*	*14.98*	*5.57*	*6.07*	*-0.43*	*9.21*	*6.17*	*0.37*	*27.92*	*-0.50*	*24.83*	*27.30*	*-2.48*
Countries without liquidity regulation															
Peer effects	0.41 ***	0.22 **	0.18	0.07	0.36 **	0.47 ***	0.72 **	0.66	-0.02	0.54 ***	1.26 ***	1.42 ***	0.53 ***	0.52 ***	1.08 ***
	4.98	*2.17*	*1.27*	*0.37*	*2.23*	*3.51*	*2.48*	*1.34*	*-0.03*	*2.69*	*14.31*	*13.46*	*6.31*	*7.36*	*15.01*

Notes: t-statistics in italics. Each line shows the coefficients for peer effects for different robustness tests. Bank quartiles were defined based on banks' total assets. Top 5 referes to the banks classified as being in the top 5 by assets in each country in Bankscope. The list of SIFIs (systemically important financial institutions) is the one disclosed by the Financial Stability Board in 2011. Countries with and without liquidity regulation identified using the 2011 World Bank Regulation and Supervision Survey (based on questions about minimum liquid assets and maturity mismatches limits). Columns 1-5 show the results obtained when peer liquidity choices are considered directly in the regressions, i.e., not addressing the reflection problem. Columns 6-10 show the results of the instrumental variables regressions, where the instruments are the predicted values of peers' liquidity ratios. These predicted values result from the estimation of the regressions in Table 2.3. Columns 11-15 show the first stage estimation results for these instrumental variables regressions. All the regressions use the same control variables as those reported in Table 2.5. All regressions include year, country-year and bank fixed-effects. *** significant at 1%; ** significant at 5%; * significant at 10%.

First, we consider that it is possible to argue that peer choices should not necessarily affect the decisions of a given bank contemporaneously. To take that into account, we use lagged peer effects instead. The results obtained are very similar.

An additional possibility is to consider that banks focus on peer groups outside borders, implying that the lender of last resort may not be the only motive for excessive risk-taking in liquidity management. For example, large international players may follow similar strategies because they are competing to achieve higher returns on equity, possibly through riskier funding and liquidity strategies. To test this additional hypothesis, we consider as peers all the other banks of the same size quartile, regardless of their country of origin. This hypothesis seems to be implausible, as peer effects are not statistically significant in any of the indicators analyzed. Collective risk taking strategies seem to play a role mainly at the national level, possibly reflecting common lender of last resort incentives previously discussed.

Another possibility is that the lender of last resort may only be willing to support banks that are too big or to systemic to fail, even if several banks are taking risks at the same time. Hence, it is possible that herding incentives are stronger for larger banks. To test this hypothesis, we run our regressions only for the largest banks in the sample, defined as those in the fourth quartile of the total assets distribution in each country. The results are slightly weaker than for the baseline specification. Peer effects are not significant in the liquidity creation indicator for this group of banks, but, in contrast, they become significant in the NSFR.

A bank that is very large within borders may be a small bank in international terms. This should be especially relevant in smaller countries, with smaller banking systems. We might argue that large internationally active banks could also act as a peer group. To take that into account, we estimate the same regressions for the largest banks, but now defined as those in the fourth quartile of the worldwide total assets distribution. We also find evidence of peer effects, most notably for the loan to deposit and the liquidity ratios.

To further examine the role of peer effects amongst larger banks, we compare peer effects estimates for banks above the median to those below. The statistical significance of peer effects is more robust for the largest banks, though there is also significant evidence of herding among the smaller banks. In turn, when only the five largest banks in each country are considered, the results become slightly weaker (peer effects are significant only for the loan to deposit ratio).

Even though the pre-crisis debate on systemic risk focused essentially on bank size, the global financial crisis made clear that a small or medium-sized institution can also be systemic if, for instance, it is too-interconnected-to-fail. Given this, size may be an imperfect measure of systemic risk. Indeed, the Basel Committee considers that systemically important banks should be identified using five different sets of indicators, taking into account i) cross-jurisdictional activity, ii) size, iii) interconnectedness, iv) substitutability, and v) complexity[23]. Each set of indicators has an equal weight of 20%. That said, size is only one of the dimensions that allow identifying a systemically important institution. However, the other four dimensions rely on a set of indicators that are generally not publicly available. Against this background, we also considered the list of systemically important financial institutions (SIFIs) recently disclosed by the Financial Stability Board, in order to test whether there are significant peer effects within this group of banks. The results are slightly weaker than for the initial large banks definition, remaining statistically significant and positive only for the liquidity ratio. In addition, we also considered the set of banks that belong to the Euribor panel, which may be seen as an alternative list of systemic financial institutions. In this case, the results are marginally significant only for the NSFR.

In sum, when we consider stricter definitions of large banks, such as banks

[23] http://www.bis.org/publ/bcbs255.pdf.

that are classified among the top 5 in each country, banks belonging to the systemically important financial institutions (SIFIs) list recently disclosed by the Financial Stability Board or banks in the Euribor panel, the results are relatively weaker. This result is not surprising, as these are the banks that have fewer incentives to engage in collective risk-taking strategies. Indeed, these very large banks are generally too-big-to-fail, benefiting permanently from implicit bailout guarantees. As such, these banks are the ones who face lower incentives to engage in riskier strategies when other banks are doing so, given that their probability of being bailed out hardly changes. Indeed, when we exclude the top five banks from the estimation, the results remain virtually unchanged, thus showing that herd behavior is not dominated by the largest banks.

Given these results, another important dimension to test is whether small banks tend to replicate the behavior of the larger banks. Using different definitions of small and large banks, we obtain evidence of significant peer effects, most notably for the loan to deposits, interbank, and liquidity ratios. Interestingly, we obtain negative peer effects in some specifications for liquidity creation and for the NSFR. This means that, in these cases, small banks actually decrease liquidity risk when the largest banks are increasing it.

Given the strong financial integration in the euro area, we also test whether banks operating in euro area countries behave as a peer group. The results are consistent with the baseline specification.

Finally, another potentially relevant issue is whether having in place some form of liquidity regulation affects the strategic interactions between banks. To address this issue, we use the 2011 World Bank Regulation and Supervision Survey, which includes two questions on liquidity regulation (namely, on whether countries have regulation on minimum liquid assets or on maximum maturity mismatches). The results are presented at the bottom of Table 2.7 and are not conclusive. For countries with liquidity regulation, we find statistically significant peer effects in the loan to deposit, liquidity and liquidity creation ratios. In turn, for countries without such regulation, peer effects seem to be relevant in the loan to deposit and interbank ratios, as well as for the NSFR. As such, peer effects seem to exist, regardless of the existence of liquidity regulation.

Peer effects by year In Section 2.3.3, we looked into the evolution and dispersion of liquidity indicators in the run up to the global financial crisis, observing that there was a general deterioration in several liquidity indicators during this period. Furthermore, in Table 2.4 we computed herding statistics for all the years in the sample, finding that there were statistically significant strategic interactions during most of the period analyzed. In this subsection, we estimate peer effects for each year. The results are presented in Table 2.8.

Table 2.8 - Peer effects by year

	Bank peer effects - country year peer group - (IV = predicted values of rivals' liquidity ratios) Second-step regressions									
	Loan to deposits		Interbank ratio		Liquidity ratio		Liquidity creation		NSFR	
	(1)		(2)		(3)		(4)		(5)	
Full sample	0.39	***	0.81		0.72	***	0.56	***	0.36	
	6.64		*1.09*		*8.88*		*9.02*		*1.08*	
2003	0.28	**	0.08		0.46	***	0.52	***	0.14	*
	2.06		*0.15*		*9.75*		*8.44*		*1.92*	
2004	0.27	**	-0.89		0.48	***	0.38	***	0.18	**
	2.06		*-0.97*		*8.48*		*4.89*		*2.04*	
2005	0.38	***	0.18		0.63	***	0.51	***	0.03	
	2.62		*0.65*		*12.01*		*6.49*		*0.44*	
2006	0.66	***	0.21		0.63	***	0.68	***	-0.04	
	8.26		*0.83*		*18.63*		*12.93*		*-0.94*	
2007	0.52	***	0.33		0.54	***	0.74	***	-0.08	*
	6.68		*1.46*		*14.90*		*14.01*		*-1.66*	
2008	0.62	***	0.39	*	0.51	***	0.76	***	0.09	**
	10.12		*1.75*		*13.27*		*14.18*		*2.02*	
2009	0.41	***	0.51	**	0.64	***	0.13		0.21	***
	7.40		*2.50*		*14.37*		*1.25*		*3.69*	

Notes: t-statistics in italics. Each line shows the coefficients for peer effects for different years. All the regressions use the same control variables as those reported in Table 2.5. All regressions include year, country-year and bank fixed-effects. *** significant at 1%; ** significant at 5%; * significant at 10%.

In terms of statistical significance, there were peer effects in almost all years in the loan to deposit ratio, the liquidity ratio and liquidity creation. The results are somewhat weaker for the NSFR and much weaker for the interbank ratio.

Looking at the economic significance of the estimated peer effects, some interesting conclusions may be drawn. Indeed, peer effects were larger in the years immediately before the global financial crisis, most notably in the loan to deposit ratio, the liquidity ratio and liquidity creation. This suggests that there were indeed observable collective risk-taking behaviors right before the global financial crisis, which possibly made banks more vulnerable to the shocks they were later faced with. It is also interesting to note that there were significant peer effects during the crisis years, when banks were simultaneously reshaping their balance sheets to manage risks in the new environment in which they were operating, marked by heightened funding pressures and deleveraging incentives.

Summing up Looking across the board at the extensive robustness analysis conducted, peer effects seem to be more apparent in some liquidity indicators.

The results are stronger for the loan-to-deposit ratio, which is perhaps the simplest indicator of the five considered. When other banks rely more on wholesale funding, each bank individually tends to replicate the behaviors of its peers. It should be noted that we are controlling for country-year fixed effects. As such, this result is not being affected by changes in aggregate demand, neither by changes in the cost of wholesale funding. Furthermore, by using bank fixed effects, we are also controlling for bank-specific loan and deposit demand, as well as by its cost of funding.

Together with the loan-to-deposit ratio, the liquidity creation measure and the NSFR also capture the structural liquidity position of a bank. Even though the results do not seem to be very strong for the NSFR, peer effects are also quite robust for the liquidity creation indicator. When other banks are creating more liquidity, each bank seems to follow along. Again, demand effects are controlled for with the country-year fixed effects.

Peer effects are also quite robust for the liquidity ratio. As discussed above, this ratio may be considered a close proxy for the new Basel III liquidity coverage ratio (LCR), which will be under close scrutiny by market participants and regulators. Banks hold less liquidity buffers or rely more on short-term funding when other banks do the same.

Finally, the results for the interbank ratio are relatively weak. This is not surprising, as interbank ratios can change easily overnight and, moreover, end-of-year figures may sometimes be misleading.

All in all, our results show that there are significant and consistent peer effects across different dimensions of liquidity risk, most notably in what concerns banks' reliance on wholesale debt markets, their ability to create liquidity through maturity transformation and their holdings of liquid assets. Macroprudential authorities should therefore accompany these dimensions of risk-taking, as these collective behaviors substantially aggravate systemic risk.

2.6 Concluding remarks

Banks' liquidity risk was at the core of the global financial crisis since its early days. By transforming liquid liabilities (deposits) into illiquid claims (loans), banks are intrinsically exposed to funding liquidity risk, though this risk materializes only occasionally. In this paper we provide empirical insight on how banks manage their liquidity risk and consider explicitly the role of collective risk-taking strategies on herding behavior. Indeed, when other banks are taking more risk, any given bank may have incentives to engage in similar strategies.

By adapting the herding measure proposed by Lakonishok et al (1992) to our setting we find that there was strong herding behavior in the pre-crisis period, reflected in a broad deterioration of liquidity indicators. Herding persisted though the crisis, as banks simultaneously adjusted their business models.

Given the limitations of this herding measure, we extend our analysis to a multivariate setting. However, the empirical estimation of these peer effects amongst banks in such a framework raises some econometric challenges. Based on the arguments put forth by Manski (1993), if we consider that peer choices may affect the decisions of a specific bank, we cannot rule out that the decisions of that bank will not, in turn, affect the choices made by peers (reflection problem). To overcome this critical identification problem we use as an instrumental variable the predicted values of liquidity indicators of peer banks based on the regressions of the determinants of liquidity indicators. These predicted values depend only on observable bank characteristics and should thus be orthogonal to systematic or herding effects. Using this methodology we can find evidence of significant peer effects, which is strengthened by extensive robustness tests.

Our results provide an important contribution to the ongoing policy debate. These collective risk-taking behaviors call for regulation to adequately align the incentives and minimize negative externalities. The collective behavior of banks transforms a traditionally microprudential dimension of banking risk into a macroprudential risk, which may ultimately generate much larger costs to the economy.

The new Basel III regulatory framework represents a huge step forward in the international regulation of banks. At the microprudential level, new liquidity requirements are going to be gradually imposed, reducing excessive maturity mismatches and ensuring that banks hold enough liquid assets to survive during a short stress period. However, our results suggest that there may be a missing element in the new regulatory framework: the systemic component of liquidity risk. The new liquidity risk regulation will ensure that, at the microprudential level, institutions are less exposed to liquidity risk. Nevertheless, additional macroprudential policy tools may eventually be considered to mitigate the incentives for collective risk-taking strategies. These may include tighter (cyclical or sectoral) liquidity regulation or limits to certain types of exposures or funding sources. Moreover, a well functioning resolution and bail-in framework is critical to mitigate bail-out expectations.

2.7 Appendix

	Liquidity creation		NSFR
	Classification	Weights	Weights
Residential Mortgage Loans	SL	0	0.65
Other Mortgage Loans	SL	0	0.65
Other Consumer/ Retail Loans	SL	0	0.85
Corporate & Commercial Loans	I	0.5	0.85
Other Loans	I	0.5	0.85
Less: Reserves for Impaired Loans/ NPLs			-1.00
Net Loans			
Loans and Advances to Banks	SL	0	0.50
Reverse Repos and Cash Collateral			0.00
Trading Securities and at FV through Income			0.50
Derivatives			0.50
Available for Sale Securities			0.50
Held to Maturity Securities			1.00
At-equity Investments in Associates			1.00
Other Securities			1.00
Total Securities	L	-0.5	
Investments in Property	I	0.5	1.00
Insurance Assets	I	0.5	1.00
Other Earning Assets	I	0.5	1.00
Total Earning Assets			
Cash and Due From Banks	L	-0.5	0.00
Foreclosed Real Estate	I	0.5	1.00
Fixed Assets	I	0.5	1.00
Goodwill	I	0.5	1.00
Other Intangibles	I	0.5	1.00
Current Tax Assets	I	0.5	1.00
Deferred Tax Assets	I	0.5	1.00
Discontinued Operations	I	0.5	1.00
Other Assets	I	0.5	1.00
Total Assets			

	Liquidity creation		NSFR
	Classification	Weights	Weights
Customer Deposits - Current	L	0.5	
Customer Deposits - Savings	L	0.5	
Customer Deposits - Term	SL	0	
Total Customer Deposits			0.85
Deposits from Banks	L	0.5	0.00
Repos and Cash Collateral	L	0.5	0.00
Other Deposits and Short-term Borrowings	L	0.5	0.00
Total Deposits, Money Market and Short-term Funding			
Total Long Term Funding	I	-0.5	1.00
Derivatives	L	0.5	0.00
Trading Liabilities	L	0.5	0.00
Total Funding			
Fair Value Portion of Debt	SL	0.0	0.00
Credit impairment reserves	SL	0.0	0.00
Reserves for Pensions and Other	SL	0.0	0.00
Current Tax Liabilities	SL	0.0	0.00
Deferred Tax Liabilities	SL	0.0	0.00
Other Deferred Liabilities	SL	0.0	0.00
Discontinued Operations	SL	0.0	0.00
Insurance Liabilities	SL	0.0	0.00
Other Liabilities	SL	0.0	0.00
Total Liabilities			
Pref. Shares and Hybrid Capital accounted for as Debt	I	-0.5	1.00
Pref. Shares and Hybrid Capital accounted for as Equit	I	-0.5	1.00
Total Equity	I	-0.5	1.00
Total Liabilities and Equity			

Notes: Liquidity creation is a proxy of the liquidity indicator proposed by Berger and Bouwman (2009). The higher this variable is, the more liquidity a bank is creating, i.e., the larger is its maturity transformation role. The variable is defined as:

$$
\begin{aligned}
liq\_creation \; = \; & \{1/2 * illiq\_assets + 0 * semi\_liq\_assets - 1/2 * liq\_assets\} \\
& + \{1/2 * liq\_liab. + 0 * semi\_liq\_liab. - 1/2 * illiq\_liab.\} \\
& -1/2 * capital
\end{aligned}
$$

Assets and liabilities are classified as liquid, semi-liquid or illiquid based on the criteria used by Berger and Bouwman (2009). The classification for each accounting item is displayed in the table above. Some assumptions were made, as the accounting classification is not identical to the one used in Berger and Bouwman (2009). We consider liquidity creation as a percentage of total assets.

NSFR is an approximation of the Net Stable Funding Ratio defined in Basel III, which considers the available stable funding relative to the required stable funding (i.e., assets that need to be funded). The higher this ratio is, the more comfortable is the institution's liquidity position. It is defined as:

$$NSFR = \frac{available\_stable\_funding}{required\_stable\_funding} * 100$$

Each accounting item was given a weight based on the Basel Committee's guidelines. However, it is important to note that this is a rough approximation, as the accounting data available on Bankscope does not allow to accurately classify all the items. The weights chosen are presented in the table above.

CHAPTER 3

3 Credit risk drivers: evaluating the contribution of firm level information and of macroeconomic dynamics

3.1 Introduction

Understanding the determinants of credit risk is a major issue for financial stability[24]. Banks and other financial intermediaries try to maximize their profits, which requires an accurate pricing of the risks contained in their assets portfolios. Given the weight loans to firms have on banks' assets, understanding why do some firms default, while others do not, may be a very important question to address. A clearer understanding of credit risk drivers may help to predict if and when will a firm default on its credit liabilities. Against this background, it is interesting to understand if credit default risk is mostly driven by idiosyncratic or by systematic factors (or both). On one hand, firm-specific

[24] This chapter is based on Bonfim, D. (2009), Credit risk drivers: evaluating the contribution of firm level information and macroeconomic dynamics, Journal of Banking and Finance, 33(2), 2009, pp. 281-299.

characteristics should clearly be determinant on their decision to default on bank loans. On the other hand, it has become clearer that macroeconomic developments may also have an important role in explaining the evolution of credit risk over time. Under this setup, the main purpose of this chapter is to empirically examine the determinants of corporate credit default, taking simultaneously into account firm-specific data as well as macroeconomic information.

The results obtained show that there are some important links between credit risk and macroeconomic developments. In fact, periods of strong economic growth, which are sometimes accompanied by robust credit growth, are sometimes followed by an increase in default rates, possibly as a consequence of imbalances generated in those periods. When micro information is used to assess the determinants of loan default, it becomes clearer that the firms' financial situation is relevant to determine whether they will default on their loan commitments. However, when time effect controls or macroeconomic variables are also taken into account, the results improve considerably. The results obtained allow us to conclude that macroeconomic dynamics have an important additional (and independent) contribution in explaining why do firms default.

In the late 90's, discussions concerning the design of a new international bank capital accord, usually known as Basel II, generated a renewed interest in credit risk modeling. This capital accord (Basel Committee on Banking Supervision (2004)) proposes the use of credit risk models to determine banks' capital requirements. Banks can use internal (or external) rating models to classify borrowers according to their risk. Capital requirements can then be determined based on such credit exposure, instead of being constant per credit type, as under the previous accord. Under this new regulatory setup, it became crucial to accurately measure credit risk. On the one hand, banks must hold enough capital to limit risks for depositors and to reduce insolvency risks. On the other hand, holding excessive capital is costly and limits efficiency. This recent surge in credit risk modeling, to some extent associated with Basel II, is leading to several new contributions. A brief overview of some of the most important contributions in this field may be found in Crouhy et al. (2000), Duffie and Singleton (2003), Gordy (2000), or Saunders and Allen (2002). In order to simplify the description of these models, we can try to group them according with their required inputs. We can identify three different groups of models, using this criteria: i) models which rely mostly on accounting variables, ii) models which use mostly market information, and iii) models which use macroeconomic variables or which consider default correlation issues.

The first group of models borrows from Altman's (1968) work, even though such variables can be used under different modeling techniques. Some work in this domain includes Bernhardsen (2001), Eklund et al. (2001), Bunn and Redwood (2003) or Benito et al. (2004). It should be borne in mind, however, that most of the models here mentioned do not rely solely on accounting information.

In the second group of models (those which rely mostly on market information), we can include Merton-type approaches to credit risk modeling[25] (see, for instance, Tudela and Young (2003), Gersbach and Lipponer (2003) or even Moody's KMV model (2004)), as well as other modeling setups, such as Jarrow and Turnbull (1995), Shumway (2001) or Couderc and Renault (2005). The major drawback of such models is that, as they rely on market information, usually they can only be applied to quoted companies.

Finally, we can identify a third set of credit risk models as those which use macroeconomic variables or consider default correlation issues. Discussions resulting from the implementation of Basel II made clear that credit risk varies over time and, most notably, it varies with overall macroeconomic conditions. The main idea is that most risk is built up during upturns, when banks apply looser credit standards. However, most of the risk materializes only when the economy hits a downturn. Some authors, such as Pederzoli

[25] Merton (1974) introduced the idea of applying option pricing theory to the valuation of risky bonds and loans (by modelling loans as zero-coupon bonds with fixed maturities). In this model, a borrower will have an incentive to default whenever the market value of the firm becomes lower than the amount borrowed.

and Torricelli (2005), Jiménez and Saurina (2006), Kent and D'Arcy (2001) or Borio et al. (2001) argue that high default rates during recessions are just a materialization of the risk that is built up during expansions, most notably when strong economic growth is accompanied by the creation of unsustainable financial imbalances. It should therefore be emphasized that there is a large difference between potential and observed risk[26].

Our objective is to evaluate simultaneously the effects of some of these dimensions of corporate credit risk. In order to achieve such objective, we will consider firm-specific accounting information, as well as macroeconomic and financial data, trying to understand how do idiosyncratic and systematic risk factors influence the default process.

The remainder of the chapter proceeds as follows. In Section 3.2 we briefly present the modeling setup underlying the empirical work which will be developed further ahead. In Section 3.3 we try to understand some of the links

[26]Wilson (1998), who developed CreditPortfolioView (McKinsey's credit risk model), was one of the first authors to emphasize the role macroeconomic variables could have in explaining credit defaults, using a multi-factor model of systematic default risk. Bangia et al. (2002) also had a crucial role in demonstrating the importance of macroeconomic developments in credit risk. Allen and Saunders (2003) provide a survey of cyclical effects in existing credit risk models. Other authors who tried to consider business cycle conditions in credit risk models include Lis et al. (2000), Nickell et al. (2000), Kent and D'Arcy (2001), Lowe (2002), Berger and Udell (2004), Carling et al. (2002, 2004) or Jiménez and Saurina (2006). More recently, Foos et al. (2010) showed that loan growth is usually associated with more credit risk a few years later. During the last few years, an extensive literature on the risk-taking channel of monetary policy has flourished, arguing that banks that excessive risks in their loan portfolios when interest rates are low (Jiménez et al., 2013, Maddaloni and Peydró, 2011).

between credit risk and macroeconomic developments at an aggregate level. For that purpose, we look at correlations between the cyclical components of credit overdue and of a large set of macroeconomic and financial variables. In Section 3.4 we finally look at firm-specific evidence. In this section, we begin by describing the panel dataset used in our work. In this extensive dataset we have information for more than 30.000 Portuguese firms for the period comprised between 1996 and 2002. This dataset contains information on firms' credit liabilities as well as detailed accounting information for each firm. In order to explore the determinants of loan default at a micro level, we use two different econometric techniques. We begin by using discrete choice models to understand *why* do some firms default, but later we complement our analysis using duration models. The introduction of the time dimension encompassed in duration models may provide some additional evidence on the timing of loan default, thereby addressing the question of *when* do firms default. Finally, Section 3.5 presents some concluding remarks.

3.2 Modeling default probabilities

The theoretical modeling setup underlying the empirical analysis which will be developed in Section 3.4 draws to some extent on previous work done by Rosch (2003) and Hamerle et al. (2004). Under this modeling framework, we model the default event of firm i in period t as a random variable Y_{it} such that:

$$Y_{it} = \begin{cases} 1 & \text{if firm } i \text{ defaults in } t \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

The time-discrete hazard rate can be defined as:

$$\lambda_{it} = \text{Prob}\ (Y_{it} = 1) \tag{3.2}$$

We will consider two vectors of explanatory variables. The first one is a set of firm-specific variables, which shall account for idiosyncratic risk (Z_{it}). This vector will include contemporaneous and lagged variables regarding several dimensions of the firm's financial situation, such as age, size, asset growth, profitability, leverage and liquidity. The second vector comprises a set of aggregate time-varying regressors, which intend to account for systematic risk (X_t). These may include variables such as GDP growth, industrial production, confidence levels, credit growth, interest rates, equity prices (and their volatility) and bond spreads.

We can use a two-state one factor return generating model, which can be used under the framework of Basel II to calibrate risk weights (Rosch (2003) develops an application using a similar modeling setup). The discrete-time process for the return on a firm's assets (R_{it}), in a given period, follows a one-factor model defined as:

$$R_{it} = \sqrt{\rho}X_t + \sqrt{(1-\rho)}Z_{it} \tag{3.3}$$

where $X_t \sim N(0,1)$, $Z_{it} \sim N(0,1)$ (normalized returns assumption).

The exposure to the common factor is given by $\sqrt{\rho}$. If we consider that the idiosyncratic component is independent from the systematic factor, as well as independent across borrowers, then ρ measures the correlation between the normalized asset returns of any two borrowers.

However, these assumptions may be too strict. In fact, empirical evidence suggests that the idiosyncratic component may not always be independent from the systematic factor. Furthermore, the assumption of a unique common factor may be too poor if we want to fully understand which factors are more important in driving default probabilities. So, taking into account these considerations, the return model may be slightly adapted, yielding:

$$R_{it} = \Gamma X_t + \Delta Z_{it} \tag{3.4}$$

where Γ and Δ are parameter vectors, which can be estimated through a linear panel model such as:

$$R_{it} = \alpha + \gamma X_t + \delta Z_{it} + u_{it} \tag{3.5}$$

where α is the model constant term, γ and δ are the estimates of Γ and Δ, and u_{it} is the error-term.

The borrower will default if his returns fall below a given threshold c_{it}:

$$R_{it} \leq c_{it} \Leftrightarrow Y_{it} = 1 \tag{3.6}$$

The realization of the risk drivers X_t and Z_{it} and of the default indicator Y_{it} is observable, but the returns R_{it} are not. The link between the risk factors and the default probability can be accomplished with a threshold model. So, we can redefine the probability of default at time t for borrower i (time-discrete hazard) as:

$$\lambda_{it} = \text{Prob}\,(Y_{it} = 1) = \text{Prob}\,(R_{it} \leq c_{it}) = \tag{3.7}$$

$$= \text{Prob}\,(\Gamma X_t + \Delta Z_{it} \leq c_{it}) = \phi(c_{it})$$

where $\phi(.)$ denotes the cumulative standard normal distribution function.

Taking into account the estimated linear panel model we can write:

$$\begin{aligned}
\lambda_{it}(X_t, Z_{it}) &= \text{Prob}\left(Y_{it} = 1 \mid X_{t,} Z_{it}\right) = \\
&= \text{Prob}\left(R_{it} \leq c_{it} \mid X_{t,} Z_{it}\right) = \\
&= \text{Prob}\left(\alpha + \gamma X_t + \delta Z_{it} + u_{it} \leq c_{it} \mid X_{t,} Z_{it}\right) = \\
&= \text{Prob}\left(u_{it} \leq c_{it} - \alpha - \gamma X_t - \delta Z_{it} \mid X_{t,} Z_{it}\right) = \\
&= F(\tilde{\alpha} + \tilde{\gamma} X_t + \tilde{\delta} Z_{it})
\end{aligned} \tag{3.8}$$

where $F(.)$ denotes the cumulative distribution function of the error term, $\tilde{\alpha} = c_{it} - \alpha$ (assuming $c_{it} = c, \forall_{it}$), $\tilde{\gamma} = -\gamma$ and $\tilde{\delta} = -\delta$.

Before exploring the information available at the firm-level, we will begin by trying to draw some conclusions on the relationship between credit risk and macroeconomic information at an aggregate level. Hence, this modeling setup will be applied in Section 3.4, where we will use micro data to assess the determinants of default probabilities at the firm-level.

3.3 Credit risk and macroeconomic dynamics: an aggregate approach

Before looking at evidence provided by firm-level data, we will try to understand some of the links between credit risk and macroeconomic developments at an aggregate level. In order to achieve such objective, we built up correlation matrices between the cyclical components of credit overdue and of a large set of macroeconomic and financial variables. These matrices may provide a clearer understanding of the cyclical comovement between credit overdue and other variables, which can later be used as explanatory variables under a regression analysis framework, together with firm-specific variables.

3.3.1 Data and methodology

In order to evaluate the relationship between credit risk and macroeconomic developments, we gathered a large set of macroeconomic and financial time series. In this analysis, credit default is measured as credit and interest which have become overdue within the last 3 to 6 months. There is, however, one caveat in using this measure of credit overdue: it is not possible to separately assess the evolution of non-financial corporations' and households' credit overdue. To partly overcome this issue, estimations were also performed using the stock of non-performing loans of non-financial corporations, though this stock variable should not perform so well in capturing the dynamics of new credit overdue.

Macroeconomic and financial series include information on national accounts, inflation, labor market data, loans, loan loss provisions, interest rates and stock market prices. All time series, considered at a quarterly frequency, were detrended using the Hodrick-Prescott filter[27]. The cyclical components obtained through filtering were then used to compute correlations with our aggregate credit risk measure, considering several time lags.

3.3.2 Some results

As mentioned above, the analysis of the cyclical components of several macroeconomic and financial variables (and of their correlation with non-performing loans) may shed some light on the links between credit risk and overall macroeconomic developments. A large set of time series was taken into account. Table 3.1 reports some of the most significant correlation coefficients obtained for the period comprised between 1990Q1 and 2004Q4.

[27] The smoothing parameter was set to be 1600.

Table 3.1

Correlation coefficient of x_t with credit overdue$_{t+i}$

x_t:	i = -8	= -7	= -6	= -5	= -4	= -3	= -2	= -1	i = 0	i = 1	i = 2	i = 3	i = 4	i = 5	i = 6	i = 7	i = 8
Loans																	
Loans to non-financial corp.	-0.41	-0.32	-0.28	-0.18	-0.03	0.15	0.27	0.31	0.41	0.52	0.56	0.62	0.62	0.64	0.58	0.50	0.43
Agriculture	-0.22	-0.07	0.08	0.19	0.37	0.46	0.41	0.35	0.36	0.21	0.11	0.18	0.19	0.26	0.27	0.31	0.22
Mining	-0.27	-0.21	-0.12	-0.03	0.11	0.27	0.33	0.36	0.35	0.25	0.20	0.27	0.30	0.43	0.49	0.53	0.48
Manufacturing	-0.28	-0.17	-0.14	-0.07	0.05	0.19	0.30	0.33	0.38	0.47	0.52	0.64	0.63	0.55	0.46	0.46	0.45
Utilities	-0.38	-0.29	-0.17	-0.05	-0.01	0.04	0.09	0.08	0.15	0.23	0.31	0.41	0.37	0.48	0.54	0.60	0.51
Construction	-0.46	-0.38	-0.29	-0.14	0.02	0.15	0.26	0.33	0.41	0.45	0.50	0.54	0.53	0.54	0.51	0.40	0.26
Services	-0.38	-0.32	-0.31	-0.23	-0.08	0.14	0.25	0.30	0.41	0.55	0.58	0.60	0.61	0.65	0.60	0.47	0.40
National accounts																	
Private consumption	-0.40	-0.38	-0.40	-0.30	-0.17	-0.12	-0.04	0.12	0.27	0.21	0.23	0.40	0.52	0.56	0.59	0.69	0.74
Durables	-0.48	-0.39	-0.43	-0.36	-0.27	-0.26	-0.26	-0.19	-0.06	-0.05	0.03	0.17	0.33	0.45	0.45	0.57	0.66
Non-durables	-0.26	-0.29	-0.30	-0.20	-0.09	-0.02	0.09	0.27	0.40	0.32	0.31	0.47	0.53	0.52	0.55	0.62	0.63
Public consumption	-0.46	-0.47	-0.43	-0.36	-0.24	-0.11	-0.01	0.11	0.23	0.27	0.33	0.42	0.52	0.63	0.69	0.71	0.67
GFCF	-0.61	-0.58	-0.50	-0.46	-0.40	-0.42	-0.38	-0.33	-0.27	-0.15	0.04	0.24	0.38	0.53	0.59	0.58	0.53
Exports	-0.10	-0.03	0.03	-0.07	-0.21	-0.37	-0.42	-0.49	-0.54	-0.38	-0.29	-0.19	-0.09	-0.01	0.04	0.04	0.10
Goods	0.03	0.13	0.20	0.11	-0.05	-0.24	-0.37	-0.49	-0.54	-0.40	-0.34	-0.29	-0.19	-0.10	-0.06	-0.10	-0.05
Services	-0.37	-0.41	-0.34	-0.40	-0.42	-0.43	-0.32	-0.27	-0.31	-0.20	-0.04	0.10	0.18	0.20	0.23	0.32	0.36
Imports	-0.38	-0.31	-0.25	-0.31	-0.36	-0.47	-0.41	-0.40	-0.46	-0.34	-0.15	-0.04	0.14	0.29	0.38	0.37	0.42
Goods	-0.37	-0.28	-0.22	-0.27	-0.34	-0.44	-0.39	-0.40	-0.47	-0.36	-0.20	-0.09	0.09	0.26	0.36	0.34	0.41
Services	-0.16	-0.28	-0.28	-0.30	-0.23	-0.33	-0.31	-0.13	-0.05	-0.01	0.21	0.32	0.35	0.26	0.30	0.35	0.21
GDP	-0.52	-0.45	-0.39	-0.26	-0.14	-0.16	-0.20	-0.16	-0.04	0.08	0.14	0.35	0.42	0.45	0.47	0.56	0.57
Other economic indicators																	
Coincident indic. for econ. act.	-0.57	-0.60	-0.60	-0.59	-0.56	-0.54	-0.52	-0.45	-0.36	-0.26	-0.13	0.01	0.16	0.26	0.33	0.40	0.44
Inflation																	
CPI growth	0.08	0.24	0.17	0.15	0.21	0.28	0.29	0.45	0.58	0.54	0.37	0.37	0.42	0.35	0.16	0.11	0.15
Bank interest rates																	
Interest rate on firms	-0.15	-0.15	-0.17	-0.21	-0.24	-0.24	-0.22	-0.18	-0.13	0.10	0.24	0.27	0.35	0.29	0.25	0.25	0.30
Interest rate housing	-0.20	-0.22	-0.23	-0.27	-0.29	-0.26	-0.22	-0.17	-0.13	0.12	0.29	0.32	0.39	0.33	0.29	0.26	0.28
Interest rate households other	-0.03	-0.05	-0.12	-0.19	-0.22	-0.24	-0.24	-0.23	-0.20	0.02	0.15	0.19	0.28	0.22	0.20	0.22	0.29
Stock market data																	
PSI Geral	-0.35	-0.31	-0.36	-0.46	-0.38	-0.31	-0.39	-0.41	-0.37	-0.17	-0.07	0.00	0.16	0.11	0.03	0.06	0.27
PSI 20	-0.32	-0.26	-0.29	-0.36	-0.25	-0.14	-0.20	-0.18	-0.10	0.04	0.06	0.10	0.22	0.33	0.23	0.11	0.26
Bond yields																	
Gov bond DE 5	-0.22	-0.11	0.00	0.12	0.16	0.02	-0.10	-0.09	-0.10	-0.15	-0.15	0.04	0.22	0.33	0.39	0.42	0.34
Gov bond DE 10	-0.04	0.07	0.14	0.23	0.28	0.13	-0.02	-0.02	-0.03	-0.12	-0.16	-0.01	0.16	0.27	0.32	0.35	0.30
Gov bond EMU 10	-0.05	0.00	0.00	0.02	-0.02	-0.16	-0.26	-0.26	-0.26	-0.09	0.06	0.13	0.27	0.24	0.25	0.27	0.34

Note: This table reports correlation coefficients between the cyclical component of each listed variable at t (x_t) and the cyclical component of credit overdue at different time periods (credit overdue$_{t+i}$), using quarterly information for the period comprised between 1990Q1 and 2004Q4 (except for Government bond yields, for which only slightly shorter time series are available). This definition of credit overdue comprises credit and interest overdue for more than 3 and less than 6 months. The highest correlation for each variable is highlighted in grey. The coincident indicator for economic activity refers to the cyclical component underlying the construction of this business cycle indicator. The data source for most time series is Banco de Portugal. The only exceptions are CPI growth (INE), stock market data (Euronext) and government bond yields (Reuters).

First of all, the correlation between loans to non-financial corporations at t and credit overdue at $t+5$ is quite high and positive (0.64), as illustrated in the first panel of Table 3.1. This evidence helps to support the hypothesis that most credit risk is built up during periods of strong credit growth, materializing only when the economy hits a downturn, as discussed above (see Pederzoli and Torricelli (2005) or Jiménez and Saurina (2006), for instance). In turn, the correlation between loans to non-financial corporations at t and credit overdue at $t-8$ is also relatively high, but it is now negative (-0.41), implying that a strong growth in credit overdue at t is correlated with a contraction in total credit at $t+8$. This may suggest that banks apply tighter standards on loan approval after a period in which non-performing loans increase significantly. Moreover, in a period of economic slowdown, loan demand is expected to remain subdued.

The cyclical component of GDP displays a positive leading correlation with the cycle of credit overdue (the strongest correlation is seen between GDP at t and new credit overdue at $t+8$). This result implies that a period of robust economic growth is usually followed by an increase in new credit overdue, with a lag of at least two years. This result is also important to confirm the hypothesis that in periods of economic growth there may be some tendency towards excessive risk-taking, which materializes in an increase of credit overdue only when the economy hits a downturn. The negative contemporaneous correlation is particularly strong if we consider the stock of non-financial corporations' non-performing loans instead of the flow of new credit overdue. In sum, in periods of strong economic growth imbalances may be building up. According to our results, these imbalances start to be gradually reflected in new credit overdue with a lag of at least two years. Then, the growth of new credit overdue is progressively reflected in an increase of the stock of non-performing loans. When the cyclical component of non-performing loans reaches its peak (that is, when credit risk fully materializes), the cycle of GDP is at its trough, resulting in a strong negative contemporaneous correlation between these two variables[28].

In what concerns GDP components, the results are rather mixed. On the one hand, the cyclical component of private (and public) consumption displays a positive leading correlation with the cycle of new credit overdue. On the other hand, the cyclical components of investment (measured by gross fixed capital formation), imports and exports display a negative lagged correlation. This may suggest that credit imbalances are usually more associated with consumption-driven expansions, though this conclusion may be very sensitive

[28] Most of the empirical literature on credit risk modelling focuses on the cross-section rather than on the time-series dimension of credit risk. An exception is a recent work by Koopman and Lucas (2005), which uses a multivariate unobserved components approach to evaluate the dynamic behaviour of business failures, credit spreads and GDP in the United States, using considerably long time series (1933-1997). The authors find evidence of negative co-cyclicality between GDP and business failures for long business cycles (with an average duration of 11 years) and a positive relationship between the cyclical component of business failures and credit spreads.

to the time interval considered.

Bank interest rates display a positive correlation with the cyclical component of new credit overdue and are leading variables. In fact, their strongest correlation is seen at $t+4$, suggesting that an increase in credit overdue is often preceded by an interest rate increase. This result may be associated, on one hand, with the increase of interest rates during periods of stronger and prolonged economic growth, which are sometimes followed by an increase in credit overdue, as discussed above. Additionally, a sizeable increase in interest rates implies a higher debt service, which may put some strain on highly leveraged firms. On the other hand, when interest rates increase significantly, adverse selection problems may become more frequent, implying higher default rates some periods afterwards[29].

Government bond yields display a pattern similar to that of bank interest rates. Stock market indices exhibit a negative correlation, implying that positive developments in stock market prices, which usually reflect a broad-based improvement in firms' financial condition, are usually associated with lower default ratios, as should be expected.

The links between credit default and macroeconomic developments will be

[29] Borrowers with projects which entail relatively low risks may consider that interest rates are higher than what is deemed adequate to ensure minimum profitability levels, thus introducing a potential bias in banks' loan portfolios towards riskier borrowers.

further explored in the next section, by taking simultaneously into account firm-specific and macroeconomic variables under a regression analysis framework. The insight provided by the analysis of cyclical components will then be helpful in choosing the set of explanatory variables to be considered.

3.4 The contribution of firm level information to understand loan default

In the previous section we discussed some of the determinants of loan default at an aggregate level, using macroeconomic and financial time series. However, firm level data may provide a much richer insight of credit risk drivers.

In this section we will explore an extensive and detailed dataset which comprises information on more than 30.000 Portuguese firms. We will begin by describing the dataset, presenting some revealing summary statistics. Then we will briefly describe the econometric methodology used. First we use discrete choice models to better understand what drives firms' loan defaults. Afterwards, we complement our analysis using duration models. The time dimension encompassed in duration models allows us to focus on the time it takes for a loan to default, rather than simply considering whether or not firms default.

3.4.1 Data and summary statistics

The microeconomic dataset used in this work comprises two distinct datasets held by Banco de Portugal, namely, the Central Credit Register and the Central Balance Sheet Database. The Central Credit Register provides information on all credit exposures above 50 euro in Portugal. The information contained in this database is reported by credit institutions (reporting is mandatory) and its main objective is sharing information between participant institutions, in order to improve their credit risk assessment and management. This database contains monthly information on loans granted to firms and households, including their current status (it is possible to know whether credit has become overdue, if it was written-off banks' balance sheets, if it was renegotiated or if it is an off-balance sheet risk, such as the unused parts of credit lines or bank guarantees)[30]. Using end-of-year data for the period comprised between 1996 and 2002, we have 203.655 observations[31]. The Central Balance Sheet Database provides detailed accounting information for a large sample of Portuguese firms, being used mostly for economic and statistical purposes.

[30] Reporting banks aggregate information on loans with similar status for each firm (information is not reported on a loan by loan basis). There is no information on loan maturity, collateral or interest rates. In what concerns loan maturity, nearly half of the loans granted to non-financial corporations in the period under analysis had maturities above one year, taking into account aggregate statistics.

[31] In order to merge the two datasets, loans were aggregated within firms. Hence, one observation is defined as a pair firm-year, summing up all credit liabilities for a given firm in each year.

We use annual data, though quarterly data is also available for a smaller set of firms. Reporting is not compulsory, but the sample is considered to be representative. Nevertheless, there may exist some bias towards larger firms. Even though this bias represents a shortcoming of this database, it still is an extremely rich and unique dataset on non-financial corporations. In this dataset we have 153.581 observations for the period comprised between 1996 and 2002. Merging the two databases we obtain a dataset containing 113.119 observations, comprising 33.084 firms.

We constructed several ratios and indicators to evaluate each firms' financial situation, namely in what concerns their profitability, financial structure, leverage, productivity, liquidity and investment. In variables with significant outliers, we replaced observations above the 99th percentile with the value of that percentile (the same procedure was applied to observations below the 1st percentile, whenever necessary).

Only a small percentage of firms in the sample has credit overdue. In fact, on average, credit overdue represents only 1 per cent of total bank loans[32]. The mean value of the dummy variable credit overdue (which takes the value 1 when a firm records a loan default) can be interpreted as a historical default probability, standing at 3 per cent during the period under analysis (we observe

[32]Taking into account only those firms which actually default, credit overdue represents, on average, 34 per cent of their total loans.

3084 defaults, using end of year data).

One of our main objectives is to understand what drives credit risk at the firm-level. This can be partly accomplished by looking separately at summary statistics for firms which record a loan default at t, comparing them with the remaining firms. In Table 3.2 we present the mean values for these two groups of firms for several potentially interesting variables. A brief analysis confirms that firms with loan defaults seem in fact to differ from other firms. On average, firms in default are less profitable, show weaker sales and investment growth, have lower liquidity ratios and are more dependent on external funding sources.

Table 3.2

Summary statistics - comparing firms with and without defaults

	Mean values for firms with no default at t	Mean values for firms in default at t	Welch test - Ho: diff = 0			Ha: diff not 0	
			t-ratio	Degrees of freedom	diff = mean (no def.) - mean (def.)	Pr(|T| > |t|)	Mean is significantly different (Y/N)
ROA	0.5	-4.9	15.18	3178	5.4	0.00	Y
Sales growth	12.9	5.7	5.74	2252	7.2	0.00	Y
Solvency ratio	23.2	1.1	26.32	3171	22.1	0.00	Y
Total credit as a % assets	12.5	16.9	-12.02	3209	-4.4	0.00	Y
Leverage	76.8	98.9	-26.32	3171	-22.1	0.00	Y
Investment rate	2.6	-2.5	11.89	2248	5.1	0.00	Y
Liquidity ratio	119.0	86.5	20.75	3356	32.5	0.00	Y
Firm age	16.3	18.6	-7.52	3252	-2.3	0.00	Y
Total assets	9123577	9771957	**-0.17**	3149	-648380	0.87	**N**
Employees	53.6	59.3	-2.47	4389	-5.7	0.01	Y
Number of observations	100117	3084					

Note: total assets are in euros. ROA, sales growth, the solvency ratio, total credit as a % of assets, leverage, the investment rate and the liquidity ratio are displayed as percentages. ROA defined as net income to total assets. Sales growth is the year-on-year growth rate of sales and services; the solvency ratio is defined as equity over total assets. The investment rate is computed as the ratio between the annual variation in net fixed assets and leverage is defined as total liabilities over total assets. The liquidity ratio is defined as the ratio between liquid assets (bank deposits and cash, debt receivables, inventories and short-term investments) and debt payables.

On average, firms in default are slightly older, which is not what should be expected. There is mixed evidence in the literature in what concerns the impact of firm age. Younger firms should be more sensitive to external shocks and should be expected to show higher bankruptcy probabilities, as argued by Eklund et al. (2001), for instance. In turn, Shumway (2001) finds no evidence of duration dependence in bankruptcy probabilities (firm age is never statistically significant, after controlling for other firm characteristics). The positive correlation between firm age and default frequencies in our sample may reflect positive duration dependence: the longer the firm is at risk, the higher should be its default probability. This issue will be discussed in more detail with the results obtained using duration models.

The results also suggest that firms in default are, on average, slightly larger than the remaining firms in the sample, in contrast to what is usually seen in the literature. For instance, Bhattacharjee et al. (2009), Bunn and Redwood (2003), Eklund et al. (2001) and Jiménez and Saurina (2004) find that smaller firms are more likely to default. In turn, Pain and Vesala (2004) and Bernhardsen (2001) conclude that any systemic effect of firm size on default is relatively small. Furthermore, there is also contrary evidence on the impact of firm size in the literature. According to Moody's (2004), larger firms default less often, but when financial statement ratios are taken into account, the impact of the size advantage declines. Hence, a small firm with healthy financial ratios should not be riskier than a large firm with comparable financial statements. Finally, Benito et al. (2004) obtain a result similar to ours, observing a positive relationship between firm size and default rates (the authors argue that their database may be biased towards "good" companies, which may also be a problem in our database).

In order to more accurately test if these variables are in fact different for firms in default, we also present in Table 3.2 the results of a mean comparison

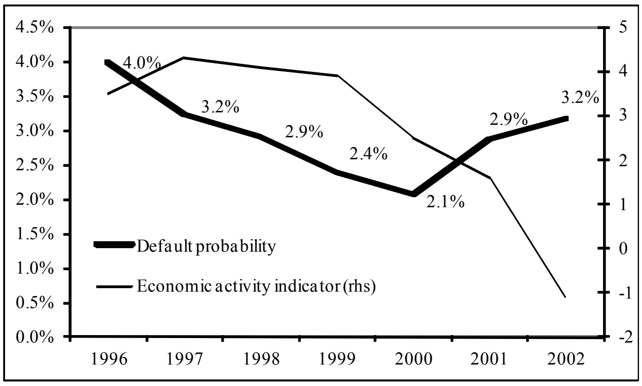
Welch test. For all variables considered, the mean values for firms in default are statistically different from the mean values observed for firms without default (with the exception of total assets, for which the mean value is not statistically different between the two groups of firms). Hence, the set of variables considered in this table may contribute to explain why do some firms default, under a regression analysis framework.

Furthermore, we also computed pairwise correlations for all the variables in the dataset, identifying which pairwise correlations are significant at a 5 per cent significance level. This correlation matrix was used as a guidance tool to choose relevant firm-specific and macroeconomic variables, as well as to identify possible multicollinearity problems between explanatory variables.

Figure 3.1 illustrates the evolution of historical default frequencies during the sample period, depicted against the economic activity coincident indicator. Until 2000, there was a steady decline in default frequencies, accompanied by positive economic developments. The deterioration of economic conditions was then mirrored (with some lag) by an increase in observed default frequencies, as well as in the amount of credit overdue as a percentage of total credit.

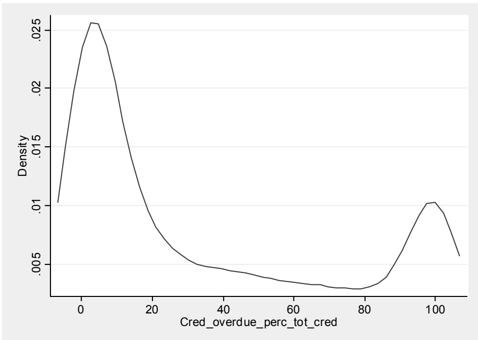
The empirical distribution of this latter ratio is depicted in Figure 3.2, using a gaussian kernel density. The distribution of this ratio is clearly two-peaked: either firms record only small amounts of credit overdue (as a percentage of

Figure 3.1: Historical default frequency



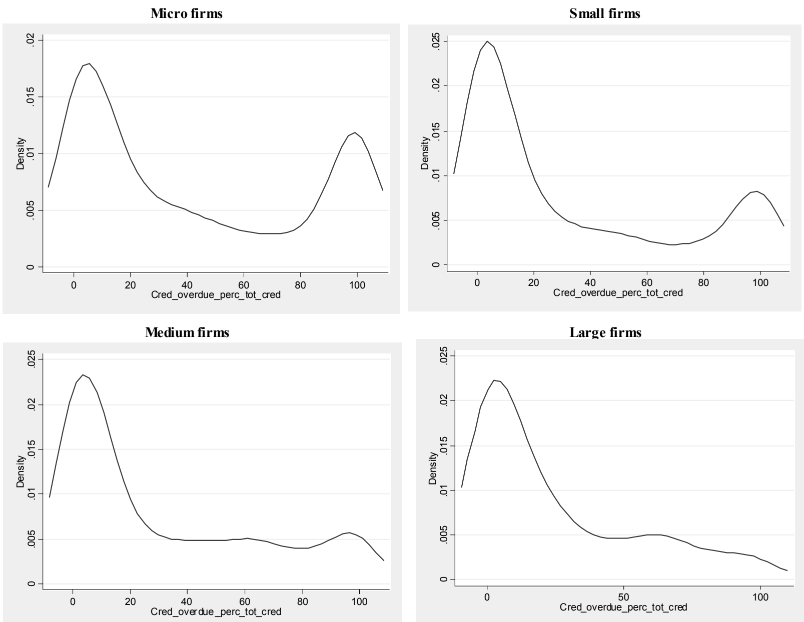
their total credit liabilities), which may reflect transitory episodes of delinquency, or they default on nearly all their debt, which should be a situation closer to bankruptcy. In this domain, it may be interesting to notice the differences seen when firm size is taken into account. As mentioned above, large and medium-sized firms display higher default rates, in contrast to what is usually found in the literature. Nevertheless, the empirical distribution of the ratio between credit overdue and total credit is remarkably different for firms with different sizes, as illustrated in Figure 3.3. In fact, whereas the distribution for micro firms is clearly two-peaked (which is, to a lesser extent, also true for small firms), the distribution for medium and, most notably, for large firms is single-peaked. This result may suggest that even though larger firms display higher default frequencies in our sample, these usually reflect small and, most likely, transitory episodes of loan default. Larger firms may have fewer difficulties in overcoming credit problems in part because banks may be more willing to renegotiate impaired loans, in order to avoid sizeable losses.

Figure 3.2: Empirical distribution function of the credit overdue ratio (gaussian kernel density)



By setting up a transition matrix, it is possible to evaluate historical default probabilities at different time horizons. In Table 3.3 (panel A) are presented average default frequencies at different time horizons and for different years. Default probabilities are fairly stable during the first years (decreasing slightly until $t + 3$), but increase considerably afterwards. Such pattern may signal positive duration dependence: the longer the firm is at risk, the higher should be its default probability. By defining conditional transition probabilities, we can trace separately the evolution of the risk profile of firms which are in default at t (Table 3.3.B). We can see that this evolution is extremely different

Figure 3.3: Empirical distribution function of the credit overdue ratio by firm size (gaussian kernel density)



for firms with and without default at t. For firms which are not in default at t, default probabilities are clearly increasing over time, which was not clear when we considered all firms in the sample. In turn, for firms which have defaulted at t, recovery probabilities (defined as 100 per cent less the default probability) are markedly increasing and larger than 75 per cent after 6 years. Finally, we can also build conditional transition matrices for firms without any prior default (in the sample period) and also for firms which did not default at t, but which recorded at least one previous default episode in the sample period, as depicted in Table 3.3.C (this latter group has a very limited number of observations). Default probabilities seem to be slightly lower for firms without any previous default in the sample period, though their time evolution is similar to those with no default at t. In turn, for firms which are not in default at t but had some previous default in the sample period, default probabilities are considerably higher, implying that firms with a past record of credit overdue are more likely to default again in the future than firms that never defaulted before.

Table 3.3

A - Transition matrix

	Default probabilities at different time horizons (%)						
	t	t+1	t+2	t+3	t+4	t+5	t+6
1996	**3.99**	3.51	3.29	2.61	2.29	3.41	3.73
1997	**3.23**	3.13	2.54	2.26	3.39	3.63	-
1998	**2.90**	2.51	2.22	3.30	3.52	-	-
1999	**2.38**	2.12	3.14	3.41	-	-	-
2000	**2.07**	3.00	3.26	-	-	-	-
2001	**2.86**	3.24	-	-	-	-	-
2002	**3.16**	-	-	-	-	-	-
Average	**2.99**	**2.95**	**2.89**	**2.86**	**3.04**	**3.52**	**3.73**

B - Conditional transition matrix

	Default probabilities at different time horizons (%)						
	t	t+1	t+2	t+3	t+4	t+5	t+6
Firms with no default at t	0.00	1.63	2.06	2.23	2.57	3.07	3.34
Firms in default at t	100.00	54.62	42.41	36.72	31.45	30.04	23.97
Average	2.99	2.95	2.89	2.86	3.04	3.52	3.73

C - Transition matrix for firms with and without default

	Default probabilities at different time horizons for firms without any prior default (%)						
	t	t+1	t+2	t+3	t+4	t+5	t+6
1996	0.00	1.52	2.13	1.81	1.65	2.84	3.34
1997	0.00	1.53	1.51	1.44	2.72	3.19	-
1998	0.00	1.19	1.23	2.61	2.98	-	-
1999	0.00	0.83	2.19	2.67	-	-	-
2000	0.00	1.95	2.42	-	-	-	-
2001	0.00	1.91	-	-	-	-	-
2002	0.00	-	-	-	-	-	-
Average	0.00	1.48	1.89	2.09	2.42	3.01	3.34

	Default prob. at different time horizons for firms without default at t but with prior defaults (%)						
	t	t+1	t+2	t+3	t+4	t+5	t+6
1996	-	-	-	-	-	-	-
1997	0.0	8.5	8.3	6.9	16.0	13.1	-
1998	0.0	9.5	12.9	14.6	17.6	-	-
1999	0.0	10.1	13.7	15.9	-	-	-
2000	0.0	12.8	16.8	-	-	-	-
2001	0.0	12.9	-	-	-	-	-
2002	0.0	-	-	-	-	-	-
Average	0.0	10.9	13.4	13.4	16.9	13.1	-

3.4.2 Econometric methodology

A common approach in the empirical credit risk literature is to use standard discrete choice models, such as logit or probit models (see, for instance, Benito et al. (2004), Bernhardsen (2001), Bunn and Redwood (2003), Hamerle (2004) or Campbell et al. (2008))[33]. These models can be used to empirically examine credit risk drivers, assessing their relative importance in determining whether firms default on their credit liabilities. Recalling equation 3.8, we want to estimate a linear panel model such as:

$$\begin{aligned}\lambda_{it}(X_t, Z_{it}) &= \text{Prob}\left(Y_{it} = 1 \mid X_{t,} Z_{it}\right) = \\ &= F(\tilde{\alpha} + \tilde{\gamma} X_t + \tilde{\delta} Z_{it})\end{aligned} \tag{3.9}$$

The model to be estimated will depend on the assumption made on the error distribution function $F(.)$. Assuming a standard normal distribution function $\Theta(.)$ yields a probit model such that:

[33] For details on discrete choice modelling under a panel data framework see Wooldridge (2002), Hsiao (1986), Baltagi (1995) and Maddala and Rao (1996).

$$\lambda_{it}(X_t, Z_{it}) = \Theta(\tilde{\alpha} + \tilde{\gamma} X_t + \tilde{\delta} Z_{it}) \tag{3.10}$$

Discrete choice models may provide an interesting assessment of the determinants of loan default, helping to determine whether or not a firm with given characteristics is likely to default. However, it would also be important to focus on the time dimension of default, understanding not only if a firm will default, but also when will that eventually occur. The timing of loan default is important for establishing a complete risk evaluation, as well as for accurate loan pricing and provisioning. Duration models directly model the survival time of a loan, taking as a dependent variable the time until default. Although not so common, there are some applications of survival analysis to credit risk modeling, such as Banasik et al. (1999), Carling et al. (2002, 2004) or Couderc and Renault (2005)[34].

Duration models may have some advantages over discrete choice models, given that they can more easily incorporate the progressive deterioration of a firm's financial situation before default, as they control for each firm's time at risk, as argued by Shumway (2001). In addition, empirical evidence suggests that there may be duration dependence in default risk: firm age (or time at

[34] Shumway (2001), Bhattacharjee *et al* (2009), Roszbach (2004) and Antunes (2005) also use duration models, but to address slightly different issues of credit risk.

risk) may be an important explanatory variable, as found by Carling et al. (2002, 2004)[35]. Therefore, traditional logit and probit models, which imply constant hazard rates, may be less accurate than duration models[36]. Furthermore, the explicit introduction of the time dimension in duration models may provide better results when taking into account macroeconomic variables, as argued by Bhattacharjee et al. (2009). Despite all the advantages provided by duration models, their application to our dataset is somewhat limited, given that there is a strong left censoring problem: most firms in the dataset were created before 1996, implying that firms' time at risk is, for most observations, much larger than the observation period. Though econometric software can handle this, it still limits the conclusions to be drawn from duration models. Hence, duration models will be used mostly to complement and verify the empirical findings obtained with discrete choice models.

Under the duration modeling framework, we define T as the time until a loan defaults[37]. The hazard function can be defined as the probability of a firm defaulting on a short interval $[t, t + dt)$, conditional on not having defaulted before:

[35] As discussed in the previous sub-section, in our dataset there seems to be evidence in favor of positive duration dependence, given that older firms display higher default frequencies.

[36] Nevertheless, the inclusion of a duration variable, such as firm age, in logit or probit models, should yield results similar to those obtained with duration models.

[37] Lancaster (1990) provides one of the most complete presentations of duration models. Wooldridge (2002) also provides a brief introduction to these models under a panel data framework.

$$h(t) = \lim_{dt \to 0} \frac{\text{Prob}(t \leq T < t + dt \mid T \geq t)}{dt} \tag{3.11}$$

The hazard function represents an instantaneous rate of default per unit of time. The duration distribution function can be defined as $F(t\ )$=Prob($T < t$). The survival function is the probability of surviving up to t, and can be defined as:

$$S(t) = \text{Prob}(T \geq t) = 1 - F(t) = \exp\left\{ -\int_0^t h(s)d(s) \right\} \tag{3.12}$$

Whenever T has an exponential distribution, the hazard function $h(t)$ is constant. When the hazard function is not constant, the underlying process is said to exhibit duration dependence. If $\frac{\delta h(t)}{\delta t} > 0$, $\forall t$, there is positive duration dependence, which implies that, in our framework, the probability of default increases with time, for firms which have never defaulted before. If, on the contrary, $\frac{\delta h(t)}{\delta t} < 0$, $\forall t$, there is evidence in favor of negative duration dependence (the longer the firm has remained without defaulting, the lower should be its default probability).

If firms were homogenous, the setup described above could be directly applied. However, we want to focus on the opposite assumption, understanding which firms' specific characteristics determine their default probabilities, as well as their timings. As a consequence, assuming that we have two vectors of time-varying covariates, X_t and Z_{it} (a systematic and a firm-specific component), we must slightly adapt the specifications presented above, such that:

$$h(t, X(t), Z(t)) = \lim_{dt \to 0} \frac{\text{Prob}(t \leq T < t + dt \mid T \geq t, X(t + dt), Z(t + dt))}{dt} \tag{3.13}$$

where $X(t)$ and $Z(t)$ are the covariates path up to t[38].

We begin our survival regression analysis by using a Cox proportional hazard model, such that:

$$h(t, X(t), Z(t)) = \kappa(X(t), Z(t))h_0(t) \tag{3.14}$$

where $\kappa(.)$ is a non-negative function of $X(t)$ and $Z(t)$, and $h_0(t)$ is defined as the baseline hazard, which is common to all firms (individual hazard functions differ from each other proportionally, as a function of $\kappa(X(t), Z(t))$. This is a partly non-parametric approach, given that we can estimate unknown parameters of $\kappa(.)$ without specifying the form of the baseline hazard. Under this setup, the regressors do not affect the shape of the overall hazard function,

[38]It is important to make a distinction between exogenous and endogenous regressors. According to Lancaster (1990), a covariate process $\{x(t)\}$ is exogenous for T if and only if Prob$(X(t, t{+}dt) \mid T \geq t{+}dt, X(t))$ =Prob$(X(t, t{+}dt \mid X(t))$. This means that any regressor whose path is determined independently of whether any particular agent has defaulted or not is exogenous. In our work, all variables used (both time-variant and time-invariant) will be considered exogenous.

conditioning only the relative failure risk of each firm.

We then extend our analysis by estimating parametric duration models, using several different distribution functions (namely, exponential, Weibull, Gompertz, lognormal, and log-logistic).

3.4.3 Results

Results obtained using discrete choice models In Table 3.4 we present some of the results obtained using a random-effects probit. The first results presented in this table focus on 71.058 observations, for 24.668 different firms, though the full sample comprises 113.119 observations for 33.084 firms (on average, we have 3 years of observations for each firm). This difference results from using variables constructed with information on the previous year (such as sales growth or the investment rate), which excludes from the regressions all observations for 1996, as well as those which do not have two consecutive years of information. Furthermore, several observations have missing values in some of the variables used, being also naturally excluded from the regression analysis (which explains the slightly different number of observations in some of the models presented). Additionally, we are excluding from the regression analysis firms in default for at least two consecutive years, considering only their first default observation, in order to evaluate only new transitions into the default state (if, however, a firm defaults twice or more during the sample period, but in non-consecutive years, these defaults will be considered as new transitions).

Table 3.4 - Probit regressions (dependent variable : dummy credit overdue)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Sales growth	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	-0.001
	-2.28	*-2.68*	*-2.19*	*-2.20*	*-2.16*	*-1.79*	*-2.18*	*-2.52*	*-0.47*	*-1.97*
ROA	-0.005	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	-4.73	*-4.34*	*-3.96*	*-3.95*	*-3.92*	*-3.75*	*-3.93*	*-3.97*	*-4.05*	*-3.66*
Solvency ratio	-0.004	-0.004	-0.005	-0.005	-0.005	-0.006	-0.006	-0.006	-0.007	-0.006
	-6.52	*-7.15*	*-7.56*	*-7.35*	*-7.36*	*-11.16*	*-11.23*	*-11.24*	*-11.87*	*-11.09*
Investment rate	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005		-0.005	-0.005
	-5.38	*-5.35*	*-5.01*	*-4.99*	*-4.99*	*-4.44*	*-4.82*		*-5.18*	*-4.52*
Liquidity ratio	-0.002	-0.001	-0.001	-0.001	-0.001					
	-5.24	*-4.56*	*-4.47*	*-4.48*	*-4.51*					
Firm age					0.001					
					0.63					
Capital productivity						0.000				
						-2.64				
K_L coefficient							0.000			
							4.11			
Share of tangible assets								-0.002		
								-1.49		
Turnover ratio									-0.003	
									-12.01	
Available collateral (aprox.)										0.001
										1.51
Small				-0.044	-0.035	-0.048	-0.006	-0.035	-0.034	-0.044
				-0.52	*-0.41*	*-0.58*	*-0.07*	*-0.42*	*-0.41*	*-0.53*
Micro				-0.013	-0.001	-0.027	0.014	-0.011	-0.059	-0.025
				-0.15	*-0.01*	*-0.32*	*0.16*	*-0.13*	*-0.69*	*-0.29*
Medium				-0.026	-0.022	-0.025	0.007	-0.015	-0.005	-0.023
				-0.30	*-0.25*	*-0.28*	*0.07*	*-0.17*	*-0.06*	*-0.27*
1997			-0.303	-0.303	-0.302	-0.313	-0.291	-0.312	-0.284	-0.313
			-5.61	*-5.59*	*-5.56*	*-5.76*	*-5.38*	*-5.76*	*-5.25*	*-5.76*
1998			-0.229	-0.230	-0.228	-0.235	-0.220	-0.236	-0.206	-0.235
			-4.55	*-4.55*	*-4.50*	*-4.65*	*-4.36*	*-4.68*	*-4.09*	*-4.65*
1999			-0.340	-0.341	-0.339	-0.342	-0.330	-0.343	-0.329	-0.342
			-6.38	*-6.37*	*-6.34*	*-6.39*	*-6.18*	*-6.44*	*-6.15*	*-6.39*
2000			-0.390	-0.390	-0.390	-0.393	-0.389	-0.391	-0.391	-0.393
			-6.51	*-6.51*	*-6.51*	*-6.57*	*-6.50*	*-6.56*	*-6.50*	*-6.56*
2001										
2002			0.006	0.006	0.005	0.002	-0.001	0.011	-0.013	0.002
			0.12	*0.12*	*0.11*	*0.04*	*-0.03*	*0.21*	*-0.26*	*0.05*
Constant	-2.377	-2.296	-2.184	-2.153	-2.175	-2.245	-2.336	-2.048	-1.907	-2.304
	-36.82	*-35.88*	*-29.42*	*-20.17*	*-19.27*	*-21.55*	*-21.80*	*-11.85*	*-18.61*	*-21.12*
Number of observations	71058	71058	71058	71058	71058	71078	71406	71078	71406	71078
Number of firms	24668	24668	24668	24668	24668	24589	24731	24589	24731	24589
Sectoral dummies	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Log-likelihood	-5574.7	-5531.8	-5484.1	-5483.7	-5483.5	-5468.2	-5503.7	-5481.5	-5404.0	-5471.1
Log-likelihood of the constant only model, for this sample	-5746.11	-5746.11	-5746.11	-5746.11	-5746.11	-5721.08	-5763.56	-5719.51	-5763.56	-5763.56
Pseudo-R2	0.030	0.037	0.046	0.046	0.046	0.044	0.045	0.042	0.062	0.051
Wald Chi2	286.9	333.2	346.3	347.0	346.7	348.7	356.6	338.1	412.5	345.8
Prob > Chi2	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
rho	0.341	0.336	0.397	0.396	0.396	0.397	0.398	0.392	0.389	0.399
Prob >= chibar2	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Note: z-scores in italics. All models estimated using a random-effects probit estimator, where the dependent variable is the dummy credit overdue. The pseudo-R2 is a measure of goodness of the fit, being computed as function of the model's log-likelihood and of the log-likelihood of the constant-only model, for the sub-sample used in each estimation. The Wald test evaluates the overall statistical significance of the estimated coefficients. Finally, rho measures the proportion of the total variance resulting from the panel-level variance component. Sales growth is the year-on-year growth rate of sales and services. ROA is defined as net income to total assets and the solvency ratio is equity over total assets. The investment rate is computed as the ratio between the annual variation in net fixed assets and the liquidity ratio is defined as the ratio between liquid assets and debt payables.

Taking into account the mean comparisons between firms with and without default presented in Table 3.2, we started by performing some estimations using a limited set of variables. The pairwise correlations previously computed were also taken into account, not only to identify which firm variables are more correlated with default frequencies, but also to avoid possible multicollinearity problems. In the first model presented in Table 3.4, the set of explanatory variables comprises sales growth, return on assets (ROA), a solvency ratio, an investment rate and a liquidity indicator. Sales growth displays a negative coefficient, suggesting that firms with stronger sales growth rates should have lower default probabilities. Profitability seems to offer an important contribution in explaining why do some firms default, exhibiting also a negative coefficient, as should be expected (more profitable firms should have a more solid financial situation and, consequently, display lower default probabilities). The solvency ratio, which is defined as the ratio between equity and total assets, also suggests that firms with healthier financial conditions are less likely to default on their loan commitments. Moreover, firms with stronger investment rates also show lower default probabilities. In fact, it seems reasonable to admit that firms under financial pressure are not expected to engage in large investment projects. Finally, the liquidity ratio, defined as short-term assets as a percentage of the firm's total debt, has a negative impact on default probabilities, implying that firms facing stronger liquidity constraints may have higher difficulties in paying their debt commitments, which is consistent with the results obtained by Bunn and Redwood (2003) or Benito et al. (2004), for instance.

Even though the firm-specific variables taken into account seem to play an important role in predicting loan default, they should be seen as contingent on the firm's size, as well as on the sector in which it operates. Therefore, in model 2 we added sector dummies to our first specification (omitting the dummy variable for manufacturing firms). The results for these sector dummies suggest that there may be some differences in credit risk drivers across different sectors. Overall, the coefficients associated with firms' financial ratios remain robust. Though macroeconomic variables will be introduced further ahead, we will include for now year dummies, in order to control for any possible systematic effects (model 3). The fact that most of the coefficients for year dummies are significant gives support to the hypothesis that macroeconomic developments may also be important in explaining loan default, as thoroughly discussed in Section 3.3. Finally, we also included size dummies (model 4). Though micro and small firms seem to have lower default probabilities than larger firms, confirming the results obtained with descriptive statistics, these differences are not statistically significant. Therefore, even though larger firms display higher default frequencies in our sample, after controlling for the firm's financial situation, the effect of firm size on default probabilities does not seem to remain significant.

Departing from this latter model, we tried several other possibly interesting variables. For instance, in Section 3.4.1, we had concluded that firms with default were, on average, older than the remaining firms in the sample. However, firm age does not seem to be statistically significant under a regression analysis framework (model 5). We also tried to take into account some productivity measures, such as capital productivity, measured as the ratio of sales to tangible assets (model 6). Though significant, its marginal contribution to explain loan default is rather small. Nevertheless, it helps to confirm that more productive firms should have, on average, lower default probabilities (though the productivity measure used can be highly sensitive to the sector in which the firm operates). Given the correlation between this indicator and sales growth, the latter ceases to be significant in this estimation. We also tried to consider whether capital intensity could help predict default (model 7). Even though the associated coefficient is very small, there seems to be evidence that firms more intensive on capital than on labor should display slightly higher default probabilities. Another variable considered was the share of tangible assets on firms' total non-financial fixed assets. This variable displays a negative coefficient, implying that the higher the share of tangible assets, the lower is the default probability, after controlling for the firm's economic sector. Nevertheless, the estimated coefficient for this variable is hardly statistically significant. Additionally, firms with higher turnover ratios (defined as sales to assets) are, as expected, firms with lower default risk (nevertheless, this variable is, to some extent, correlated with sales growth, which ceases to be significant when the turnover ratio is introduced in the regression). Given that the database does not provide information on the collateral used to guarantee loans, we tried to build an approximate measure of total available collateral (tangible assets as a percentage of total assets), but it did not prove to be significant in the estimated regression models.

Though most of the variables discussed above have some explanatory power in predicting loan default, we should focus our analysis on a limited set of variables, which comprehensively cover the more important dimensions of the firm's situation. Model 4 seems to provide a reasonable compromise between these two aspects, taking into account the firm's profitability, its sales evolution, its financial structure, its recent investment policy and its liquidity position, after controlling for size and economic sector, as well as for time-effects. Hence, this model will be considered as our baseline specification and all further extensions will be built upon it.

In the lower part of Table 3.4 some additional information on the estimations performed is displayed. Both the log-likelihood and the pseudo-R2 do not change significantly across the different specifications presented, suggesting that most of these variables have similar contributions in predicting loan default[39]. According to the Wald test reported, coefficients are overall significant for the models considered. We also report ρ, which provides a measure of the proportion of the total variance resulting from the panel-level variance component (when ρ is zero, the panel-level variance component is irrelevant and hence the panel estimator should be equal to the pooled estimator).

As mentioned above, the estimations presented in Table 3.4 were obtained using a random-effects probit. For robustness purposes, we also estimated some of these models using alternative estimation procedures. We first used a population-averaged estimator instead of the random-effects estimator, obtaining minor differences in the estimated coefficients, though without any qualitative changes[40]. We have also estimated the same population-averaged

[39] The pseudo-R2 is a measure of goodness of the fit, being computed as $\frac{-\pi_0-(-\pi)}{-\pi}$, where π_0 is the log-likelihood of the constant-only model, for the sample used in the estimation, and π is the log-likelihood of the estimated regression. This ratio is a measure of the percentage of the variance on the dependent variable that is captured by the model.

[40] For a general model, the main difference between random-effects and population-averaged estimators is that the former fit the model $\text{Prob}(Y_{it} = 1 \mid X_{it}, u_i) = F(X_{it}\beta + u_i)$, whereas population-averaged estimators fit the model $\text{Prob}(Y_{it} = 1 \mid X_{it}) = G(X_{it}\beta^*)$. The subtle difference is that β and β^* are different population parameters: while the former takes into account the same firm for different values of the regressors, the latter focuses on average firm values (implying that $E(Y_{it} \mid X_{it}) = E(Y_{it} \mid X_i), \forall t$). For further details on population-averaged models (also known as generalised estimating equations (GEE) approach) please

model using robust variance estimates, yielding minor changes in some z-scores. Finally, we also tried to estimate the baseline model without imposing a panel data structure. More specifically, we estimated three additional simple probit regressions: two using clustered standard errors (one of them clustering by firms and other clustering by years) and one without any clustering procedure (which would imply admitting that all observations are independent both across time and within each firm). The results are broadly similar, with one single exception: sales growth is not statistically significant when observations are clustered only by firm and when the clustering procedure is ignored.

The different model specifications outlined in Table 3.4 help to identify some of the firm-specific determinants of loan default. However, it should also be of interest to evaluate how the firm's past performance affects its default probability, which could help predicting future defaults. Moreover, given that firm-specific data is usually available with a considerable lag, it becomes crucial to try to assess whether a firm is likely to become stressed in the future by evaluating its current financial situation. Departing from the baseline specification presented above, in Table 3.5 we present some additional regressions, using all firm-specific variables lagged by one, two, three and four years, respectively. When all firm variables are lagged by one and two years, the results

see Wooldridge (2002).

are mainly robust. Most of the coefficients on firm characteristics preserve the same signs. The most notable exception is the investment rate, which ceases to be significant when lagged. Moreover, the estimated coefficient for sales growth is not statistically significant when more than two lags are considered, suggesting that only the most recent sales performance truly conditions firms' default probabilities. There seems to be an increase in the marginal effect of profitability on credit risk, and, conversely, a decrease in the relative importance of the solvency ratio. Hence, sustained poor profitability ratios over time are a strong sign of firm distress, yielding possibly high future default probabilities. When variables are lagged by three and, most notably, by four years, there is a clear decrease in the model's quality (most variables are no longer significant and the pseudo-R2 decreases considerably), suggesting that the firm's recent performance is, as expected, much more relevant to explain loan default than its "historical" background.

Table 3.5 - Probit regressions

		Baseline specification	All firm variables lagged: 1 year	2 years	3 years	4 years	Models with several simultaneous lags	
Sales growth	*t*	-0.001	-0.001	0.000	0.001	0.001	-0.003	
		-2.20	*-2.60*	*0.23*	*1.23*	*0.99*	*-5.54*	
	t-1						-0.001	-0.001
							-2.84	*-2.59*
ROA	*t*	-0.004	-0.005	-0.006	-0.006	-0.003		
		-3.95	*-3.59*	*-3.09*	*-2.22*	*-1.32*		
	t-1							-0.005
								-3.58
	t-2						-0.003	
							-2.01	
Solvency ratio	*t*	-0.005	-0.003	-0.003	-0.002	-0.002	-0.007	
		-7.35	*-3.60*	*-3.21*	*-1.83*	*-1.68*	*-7.39*	
	t-1							-0.003
								-3.61
	t-2						0.003	
							3.22	
Investment rate	*t*	-0.005	0.000	0.002	0.000	0.000	-0.005	
		-4.99	*0.17*	*1.40*	*0.22*	*-0.10*	*-3.62*	
Liquidity ratio	*t*	-0.001	-0.002	-0.001	-0.002	-0.001	-0.002	
		-4.48	*-4.68*	*-3.25*	*-3.23*	*-2.39*	*-3.99*	
	t-1							-0.002
								-4.81
Constant		-2.153	-2.085	-2.130	-1.951	-1.756	-2.092	-2.083
		-20.17	*-17.31*	*-14.28*	*-10.88*	*-14.92*	*-16.90*	*-17.32*
Number of observations		71058	46608	30924	19831	12139	45335	46608
Number of firms		24668	17169	12135	8623	7346	16662	17169
Log-likelihood		-5483.7	-3732.2	-2557.2	-1802.0	-1323.2	-3598.3	-3732.2
Log-likelihood of the constant only model, for this sample		-5746.11	-3879.97	-2659.01	-1870.56	-1354.59	-3797.12	-3879.97
Pseudo-R2		0.046	0.038	0.038	0.037	0.023	0.052	0.038
Wald Chi2		347.0	196.4	119.0	65.4	55.7	250.2	196.2
Prob > Chi2		*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
rho		0.396	0.357	0.347	0.244	0.000	0.362	0.358
Prob >= chibar2		*0.00*	*0.00*	*0.00*	*0.02*	*1.00*	*0.00*	*0.00*

Note: z-scores in italics. All regressions include the control dummies for size, sector and year presented in Table 4. All models estimated using a random-effects probit estimator, where the dependent variable is the dummy credit overdue. The pseudo-R2 is a measure of goodness of the fit, being computed as function of the model's log-likelihood and of the log-likelihood of the constant-only model, for the sub-sample used in each estimation. The Wald test evaluates the overall statistical significance of the estimated coefficients. Finally, rho measures the proportion of the total variance resulting from the panel-level variance component.

In addition, we also tried to estimate similar models using simultaneously several time lags. First we lagged all variables up to four years, considering also the contemporaneous information, and then we gradually dropped those lags which proved not be significant. Then we tried a more restricted approach, considering only up to three year lags (and no contemporaneous information). The results are consistent with those previously described. In both cases, only one and two year lags turn out to be statistically significant, confirming that using more than three year lags gives the model much less accuracy. Profitability seems to have the highest lagged explanatory power, though the liquidity and solvency ratios also provide interesting information when lagged by one year (however, the solvency ratio shows a rather counter-intuitive positive coefficient at $t-2$). Again, the investment rate fails to be significant when lagged.

In Section 3.3 we discussed some of the links between loan default and macroeconomic and financial developments, at an aggregate level. In this section we have considered several firm characteristics that may contribute to understand why some firms default. Now, finally, we will try to simultaneously assess the role played by macroeconomic factors, together with firms' specific characteristics, by adding a set of macroeconomic variables to our panel data regressions. We considered a relatively large set of variables, taking into account some of the conclusions drawn in Section 3.3. Some of the variables tested in the regressions were GDP growth, the coincident economic activity indicator, (log) employment, loan growth, an exchange rate index, 10-year bond yields, the yield curve slope, banks interest rates applied on loans to firms, and stock market prices variation. Some of these variables did not prove to be significant or displayed unexpected signs. The most insightful results are presented in Table 3.6. From all the variables considered, the most important seem to be the GDP growth rate (with a negative contemporaneous impact on default probabilities, in agreement with what was discussed previously), the coincident economic activity indicator (which also evaluates economic conditions), loan growth (which also displays a negative coefficient) and, finally, stock market prices variation (implying, as previously discussed, that positive developments in stock market prices, which usually reflect an improvement in firms' financial conditions, are associated with lower default probabilities). All these variables display relatively high marginal effects on default probabilities. In fact, these marginal effects are considerably stronger than those obtained for firm-specific variables, showing that macroeconomic conditions are very important in explaining default probabilities.

Table 3.6 - Probit regressions with macroeconomic variables

	Baseline specification without time dummies	Baseline specification with time dummies	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	All firm and macro variables lagged: 1 year		2 years	
										Model 5	Model 6	Model 5	Model 6
Sales growth	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	-2.67	*-2.20*	*-2.12*	*-2.14*	*-2.21*	*-2.33*	*-2.18*	*-2.21*	*-0.72*	*-2.65*	*-2.59*	*0.23*	*0.23*
ROA	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.005	-0.005	-0.006	-0.006
	-4.30	*-3.95*	*-3.93*	*-3.96*	*-3.90*	*-4.16*	*-3.94*	*-3.94*	*-1.63*	*-3.60*	*-3.58*	*-3.09*	*-3.09*
Solvency ratio	-0.004	-0.005	-0.005	-0.005	-0.005	-0.004	-0.005	-0.005	-0.004	-0.003	-0.003	-0.003	-0.003
	-7.06	*-7.35*	*-7.37*	*-7.35*	*-7.34*	*-7.23*	*-7.37*	*-7.32*	*-3.08*	*-3.57*	*-3.61*	*-3.21*	*-3.21*
Investment rate	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.006	0.000	0.000	0.002	0.002
	-5.35	*-4.99*	*-4.99*	*-4.99*	*-4.91*	*-5.25*	*-4.97*	*-4.95*	*-2.45*	*0.19*	*0.17*	*1.40*	*1.40*
Liquidity ratio	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.003	-0.002	-0.002	-0.001	-0.001
	-4.52	*-4.48*	*-4.46*	*-4.47*	*-4.50*	*-4.44*	*-4.49*	*-4.49*	*-4.28*	*-4.71*	*-4.68*	*-3.25*	*-3.25*
Interest rate on loans to firms								0.026			0.111		0.117
								2.26			*4.10*		*1.66*
Yield curve slope (10 y - 3 m)							-0.159			0.043		-0.884	
							-3.43			*0.25*		*-2.85*	
Loan growth					-0.023		-0.019			-0.026	0.043	-0.129	
					-8.34		*-6.02*			*-1.45*	*3.39*	*-2.74*	
Stock market price variation						-0.002	-0.002			-0.001		-0.029	
						-4.86	*-3.48*			*-0.41*		*-4.27*	
GDP growth rate			-0.087						-0.141				
			-7.54						*-6.47*				
Coincident indicator BP				-0.061				-0.075			-0.325		-0.284
				-7.14				*-7.07*			*-5.96*		*-3.11*
Sales growth * GDP growth rate									0.000				
									-0.16				
ROA * GDP growth rate									0.000				
									-0.16				
Solvency ratio * GDP growth rate									0.000				
									-0.35				
Investment rate * GDP growth rate									0.000				
									0.26				
Liquidity ratio * GDP growth rate									0.001				
									2.81				
Constant	-2.241	-2.153	-2.093	-2.192	-1.872	-2.274	-1.755	-2.321	-1.935	-1.660	-2.983	2.664	-5.821
	-23.26	*-20.17*	*-20.38*	*-21.40*	*-17.64*	*-22.45*	*-14.57*	*-19.71*	*-16.78*	*-7.36*	*-9.15*	*1.90*	*-3.82*
Number of observations	71058	71058	71058	71058	71058	71058	71058	71058	71058	46608	46608	30924	30924
Number of firms	24668	24668	24668	24668	24668	24668	24668	24668	24668	17169	17169	12135	12135
Log-likelihood	-5531.2	-5483.7	-5500.3	-5503.9	-5494.1	-5518.6	-5487.0	-5501.4	-5495.5	-3754.0	-3732.2	-2557.2	-2557.2
Log-likelihood of the constant only model, for this sample	-5746.11	-5746.11	-5746.11	-5746.11	-5746.11	-5746.11	-5746.11	-5746.11	-5746.11	-3879.97	-3879.97	-2659.01	-2659.01
Pseudo-R2	0.037	0.046	0.043	0.042	0.044	0.040	0.045	0.043	0.044	0.032	0.038	0.038	0.038
Likelihood ratio test: model vs baseline without time dummies	-	95.0	61.8	54.7	74.3	25.2	88.4	59.7	-	-	-	-	-
Wald Chi2	333.8	347.0	330.3	327.3	345.7	323.3	344.3	338.3	336.2	181.6	196.4	119.0	119.0
Prob > Chi2	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
rho	0.336	0.396	0.393	0.392	0.384	0.371	0.395	0.383	0.395	0.331	0.357	0.347	0.347
Prob >= chibar2	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Note: z-scores in italics. All regressions include the control dummies for size and sector presented in Table 4. All models estimated using a random-effects probit estimator, where the dependent variable is the dummy credit overdue. The pseudo-R2 is a measure of goodness of the fit, being computed as function of the model's log-likelihood and of the log-likelihood of the constant-only model, for the sub-sample used in each estimation. The Wald test evaluates the overall statistical significance of the estimated coefficients. Rho measures the proportion of the total variance resulting from the panel-level variance component. The likelihood ratio test is defined as LRT = 2 x (-ln L1+ln L2), where L2 is the log-likelihood of the model specified in each column and L1 is the log-likelihood of the baseline model without time dummies. The likelihood ratio test has an asymptotic chi-square distribution, where the degrees of freedom are the number of additional parameters in the more complex model.

These first regressions were estimated by taking into account each macroeconomic variable separately, in order to minimize the losses in terms of information provided by firm heterogeneity. However, we also tried to take into account the joint effect of different macroeconomic and financial variables (models 5 and 6 in Table 3.6). In model 5 we considered loan growth, stock market prices variation and the slope of the yield curve. The slope of the yield curve, which may reflect, to some extent, expectations on future economic growth, has a strong negative marginal effect on default probabilities. When the variables considered in model 5 are lagged by one year (together with the firm-specific variables), the results are relatively disappointing, given that none of them remains statistically significant. Surprisingly, when we consider two year lags the results improve significantly (the marginal effect of the yield curve slope increases, confirming the forward-looking properties of this variable). Given the poor performance of this model when one year lags are taken into account, we estimated a different model (model 6), now considering interest rates on bank loans (which show, as expected, a positive contemporaneous coefficient), the coincident economic activity indicator and loan growth (which is automatically dropped when variables are used contemporaneously, given their high correlation). This model yields much better results when lagged by one year, but when two-year lags are used only the coincident indicator remains significant. It is interesting to notice that, contrary to what was suggested when we focused on aggregate time series in Section 3.3, the coefficient of economic growth (here proxied by the economic activity indicator) does not become positive when lagged by two years. Hence, even if at an aggregate level it seems to be clear that significant imbalances are created in periods of strong economic growth, after controlling for firm-specific characteristics this relationship is no longer apparent, possibly reflecting an asymmetric behavior of firms with different characteristics during different phases of the credit cycle.

Given that firms' financial ratios are also subject to sizeable fluctuations over the business cycle, we tried to explicitly model these co-movements by adding to the model interactions between firm-specific variables and the GDP growth rate (model 7). The only significant interaction variable is the one associated with the liquidity indicator, suggesting that these interactions do not play a crucial role in explaining default probabilities. The GDP growth rate remains significant, but the coefficients associated with sales growth and ROA cease to be statistically significant in this model. However, when these two variables are excluded from the regression, their respective interaction with the GDP growth rate turns out significant.

As mentioned above, all macroeconomic variables display relatively high marginal effects on default probabilities. To accurately assess the importance of macroeconomic conditions on default probabilities, we should begin by comparing the model without any time controls to the model with time dummies and to the models with macroeconomic variables. One important thing to notice is that the estimated coefficients and the z-scores for the firm specific variables almost do not change in all these specifications. This result suggests that the relevant information contained in macroeconomic variables is largely independent from that contained in firm specific variables. The incremental information provided by the inclusion of the time dimension can be confirmed by the significant increase in the pseudo-R2 of the model which includes time dummies, by comparison with a model without time controls. The substitution of these time dummies by specific macroeconomic variables (which can only capture part of the variation enclosed in time dummies) does not yield significant changes in the model's overall goodness of fit, suggesting that these macroeconomic variables can capture an important part of the time variation implicit in the year dummies. In order to more accurately test the role performed by the inclusion of time effects in the determination of default probabilities, we also performed likelihood ratio tests. The inclusion of year dummies allows for a significant increase in the likelihood of the model. When only one macroeconomic variable is considered (models 1 to 4), the change in the likelihood of the model is also very significant. Loan growth and GDP growth rate are the variables which have a higher impact on the model's likelihood. In fact, their explanatory power is not much lower than that of linear time controls. The additional explanatory power provided by the inclusion of three macroeconomic variables in model 5 is very similar to that of the time dummies. Hence, these results allow us to conclude that macroeconomic dynamics have an important additional (and independent) contribution in explaining why do firms default.

Finally, we performed some robustness checks, in order to test the validity of the results obtained. In the sample there are firms with multiple defaults and, as previously mentioned, only new transitions into the default state are being considered (if a firm is in default for more than two consecutive years, it is excluded from the regression as long as the default state persists). Taking into account the results obtained using conditional transition matrices, we have reasons to believe that firms with previous defaults may be riskier than other firms. To confirm this, we started by including in our sample all default observations (even if the firm is in default for more than two consecutive years). In this new sample, which includes more 391 firms, the results are generally robust, with the exception of profitability, which is no longer significant. Nevertheless, it is interesting to notice that the model's goodness of fit improves considerably. To better understand the differences in the behavior of firms with past loan defaults, we estimated a separate regression only for firms which were in default at $t-1$. For the 1.236 firms considered in this regression, credit risk drivers seem to differ significantly from the ones considered in our base sample. In fact, the only firm-specific variables that remain statistically significant are the solvency ratio and the investment rate. We further extended this sample to include firms with at least one previous default during the sample period (even if not at $t-1$). This model performs slightly better (the pseudo-R2 increases considerably, as well as the proportion of the total variance captured by the panel level component). In addition to the solvency ratio and the investment rate, sales growth also becomes significant. Hence, firms with previous defaults which record relatively low solvency ratios, low investment rates and low sales growth should be much riskier than other firms.

Also for robustness purposes, we tested the impact of slightly changing the definition of the dependent variable, by considering that there was default only when credit overdue was above 100 euro, 1000 euro or 1 per cent of total debt, in order to focus only on more serious default problems. The estimation results remain broadly unchanged, though the model's explanatory power seems to improve slightly. The strikingly bimodal distribution of the credit overdue ratio which, as illustrated on Figure 3.2, displays either very high or very low values was also taken into account in the regressions, in order to test whether these different default events are driven by the same determinants. As discussed above, low credit overdue ratios should reflect mostly transitory episodes of delinquency, which may easily be reverted. When we only take into account default events in which this ratio is below 50 per cent of the firms' total bank debt, most of the variables considered retain their explanatory power. The only exception is sales growth, which is no longer significant. In turn, when only more serious default episodes are considered (credit overdue ratio above 50 per cent), both profitability and liquidity cease to be statistically significant.

Still for robustness purposes, we considered other modeling techniques, namely an ordered probit and a simple OLS with an alternative dependent variable. Concerning the ordered probit model, we defined different levels of default severity by constructing intervals for the ratio of credit overdue to total credit. The results are broadly consistent with those previously presented, showing only minor differences in the estimated coefficients. In addition to this, we considered an alternative model where the ratio of credit overdue to total credit was the dependent variable, instead of the binary dependent variable considered so far (this model was estimated within a simple panel data OLS framework). Again, the results are fairly robust, except in what concerns the liquidity ratio, which presents a counter-intuitive positive coefficient.

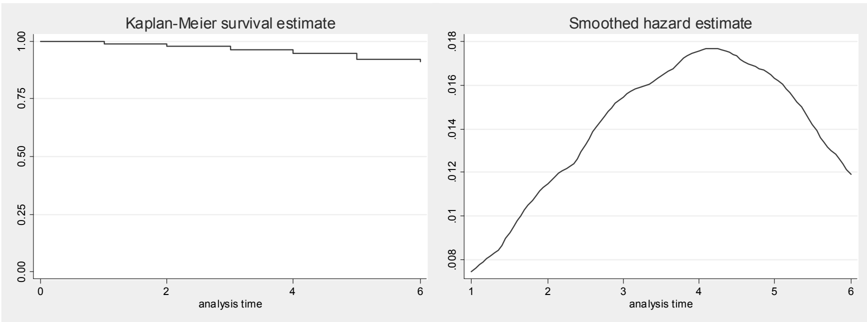
Given that reporting to the Central Balance Sheet Database is not mandatory, we may be leaving out of the regressions firms which are riskier than the average firm. It is possible to argue that reporting a balance sheet may itself be a signal of the firm's credit quality, given that small firms in financial distress may be less willing to fully disclosure information regarding their situation. In fact, default frequencies for firms which do not report to the Central Balance Sheet Database are much higher than for firms included in this database. When all these firms are considered, the default rate during the sample period increases from 3 to 5 per cent. In order to evaluate to what extent reporting a balance sheet influences default probabilities, we estimated a regression with all firms in the Credit Register. For firms for which balance sheet information was not available, mean values were considered. We included a dummy variable which takes the value one whenever the firm reported its balance sheet. This dummy variable proved to be significant and has a high explanatory variable. The negative coefficient obtained for this variable confirms that reporting a balance sheet significantly decreases default probabilities.

Recalling that we had controlled for outliers by setting observations above the 1st and 99th percentiles equal to the value of that percentile, we also tested the impact on the estimated regressions of running an alternative procedure for eliminating outliers, more specifically, by deleting the observations above or below those percentiles. The results are broadly consistent, but the change in the profitability coefficient, which becomes much stronger, should not be ignored. Finally, we also tested the introduction of some non-linearities in the model, by considering the squared value of some variables, as well as some interactions between variables. However, the marginal effect of the squared variables is almost negligible and does not seem to add much to the model. Moreover, the variable interactions tested were not statistically significant.

Results obtained using duration models The way the data are organized and declared is very important in survival analysis models. Given that our database has strong left-censoring problems, this is a particularly important issue. In fact, most firms included in the sample were created before 1996, though in our database we do not have any information about their historical record, more specifically, we do not know whether those firms have defaulted before that year. This problem can be partly accounted for by declaring that firms are considered to be at risk since their creation date, though that failure risk can be observable only after the firm enters the sample (which may eventually be after 1996). In these models, our variable of interest will be the time until default, rather than a binary variable indicating whether the firm has defaulted or not. After organizing the dataset according to these constraints, we are left with a sample of 32.966 firms, for which we have an average of 3.3 years of information. There are 1.921 observed defaults in this sample. The incidence rate, defined as the number of defaults divided by the total number of observations, is 1.8 per cent.

Given the left-censoring problems underlying our sample, we also tried to consider only those firms created from 1996 onwards, thus totally eliminating left-censoring. This implies focusing on a much smaller set of firms (3.284 firms, for which we observe only 94 defaults). The incidence rate for these firms is slightly lower, standing at 1.4 per cent. Figure 3.4 depicts several estimated functions for this subset of firms. The Kaplan-Meier survival estimate shows a steady decreasing trend, given that survival probabilities decrease over time. The most interesting results are those provided by the smoothed hazard estimate, suggesting that default probabilities are strongly increasing over time during the first 4 years of the firm's life. Afterwards, the hazard rate starts to decrease, resulting in a hump-shaped smoothed hazard estimate. These results shed some light on the previous discussions concerning the impact of firm age on default probabilities. In fact, it can be confirmed, to some extent, that default probabilities increase with firm age, though it is now clear that such increase is not linear through the firm's lifetime. Recalling from Section 3.4.2 that it can be said that there is positive duration dependence when $\frac{\delta h(t)}{\delta t} > 0$, $\forall t$ (as defined in equation 3.11), we cannot affirm that there is strictly positive duration dependence, given that for older firms we have $\frac{\delta h(t)}{\delta t} < 0$[41].

Figure 3.4: New firms



Note: analysis time in years.

Within the framework of duration modeling, we estimated several regression models, in a spirit similar to that of discrete choice models. We started by fitting Cox proportional hazard models. The results obtained, presented in Table 3.7, are broadly similar to those obtained with probit models: firms with higher sales growth, higher profitability, higher solvency, higher investment rates, and better liquidity ratios display lower default probabilities (or, to be more precise, take a longer time to eventually default on their loan commitments). However, sales growth turns out to be clearly non-significant in

[41] Estimating hazard rates for the full sample comprises significant problems, given the abovementioned left-censoring issue. Nevertheless, the estimates performed for the full sample also result in a hump-shaped hazard function. Default probabilities are clearly increasing during the first 25 years of the firm's life. Afterwards, default probabilities continue to increase, though at a less marked rate. Finally, for considerably older firms (more than 75 years), the hazard rate starts to decrease.

the estimates performed when considering robust variance estimates. Hence, though sales growth may contribute to explain why some firms default, it does not seem to determine the time until default, at least under a Cox proportional hazard specification. In contrast with what was observed when using discrete choice models, macroeconomic and financial variables are not statistically significant in these specifications. Macroeconomic conditions thus seem to be more relevant to explain why a firm defaults or not, rather than how long will it take for the firm to eventually default.

In order to confirm the legitimate use of Cox models, we tested the proportional hazards assumption. Global and individual tests for the estimated regressions provide no evidence that the proportional hazards assumption is violated.

Table 3.7 - Cox regressions (hazard ratios), robust

	Full sample			New firms								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Sales growth	0.998			1.003								
	-1.72			*1.54*								
ROA	0.995	0.994	0.994	0.992	0.992	0.992	0.993	0.993	0.992	0.992	0.993	0.992
	-4.33	*-4.83*	*-4.84*	*-2.44*	*-2.31*	*-2.31*	*-2.02*	*-1.79*	*-2.36*	*-2.37*	*-2.17*	*-2.49*
Solvency ratio	0.995	0.995	0.995	1.003	1.003		1.003	1.000	1.005	1.003	1.002	1.003
	-4.59	*-4.56*	*-4.53*	*0.74*	*0.78*		*0.74*	*-0.06*	*1.29*	*0.70*	*0.59*	*0.77*
Investment rate	0.990	0.989	0.989	0.993	0.994	0.994	0.994	0.993	0.994	0.994	0.994	0.994
	-3.94	*-4.10*	*-4.12*	*-1.23*	*-1.02*	*-1.02*	*-1.00*	*-1.47*	*-1.04*	*-1.04*	*-1.08*	*-1.02*
Liquidity ratio	0.995	0.995	0.995	0.990	0.990	0.990	0.990	0.993	0.986	0.990	0.990	0.990
	-4.53	*-4.51*	*-4.54*	*-3.94*	*-4.04*	*-4.04*	*-3.89*	*-2.97*	*-5.01*	*-3.99*	*-3.97*	*-3.98*
Leverage						0.997						
						-0.78						
Share of tangible assets							0.994					
							-0.77					
Turnover ratio								0.996				
								-2.26				
Available collateral									0.994			
									-1.32			
Activity began after 1996 (Y/N)			0.962									
			-0.23									
GDP growth rate										1.030		
										0.24		
Loan growth											0.991	
											-0.39	
Stock market price variation												1.005
												0.98
Constant	-	-	-	-	-	-	-	-	-	-	-	-
Log pseudo likelihood	-7291.3	-7294.0	-7294.3	-434.1	-435.3	-435.3	-428.4	-429.9	-428.2	-437.2	-437.2	-436.8
No. of observations	76292	76292	76292	3847	3847	3847	3802	3847	3802	3847	3847	3847
No. of subjects	25690	25690	25690	2324	2324	2324	2297	2324	2297	2324	2324	2324
No. of failures	1000	1000	1000	68	68	68	67	68	67	68	68	68
Time at risk	76292	76292	76292	3847	3847	3847	3802	3847	3802	3847	3847	3847
Wald chi2	583.9	581.4	577.9	35.7	34.2	34.2	35.2	39.9	44.8	31.5	31.0	31.3
Prob > chi2	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*

Note: z-scores in italics. New firms are defined as those created from 1996 onwards. The regressions for the full sample include the control dummies for size, sector and year presented in Table 3.4. All models estimated using a Cox regression which evaluates the time until default, using robust variance estimates. An estimated coefficient lower than 1 should be interpreted as contributing a longer time until default eventually occurs. The Wald test evaluates the overall significance of the estimated coefficients.

Given the strong left-censoring in the database, we also tested whether firms created from 1996 onwards were substantially different from others. In order to achieve that, we estimated a Cox model including a dummy variable for such firms (model 3 in Table 3.7). This dummy variable is far from being significant, suggesting that these firms do not substantially differ from the remaining firms in the sample. Nevertheless, to more deeply address this problem, we also estimated Cox regressions for this sub-sample, which are also displayed in Table 3.7. Both the solvency ratio and the investment rate cease to be significant. As argued above, these results suggest that start-up firms have relatively different determinants of loan default (in our sample, these firms show higher investment rates, as would be expected, as well as higher leverage ratios[42]). In order to complete our assessment, we tested the inclusion of other micro and macro variables. Most of the variables tested do not seem to be statistically significant in the determination of the time until default of these start-up firms. The only relevant exception seems to be the turnover ratio. Firms with lower turnover ratios should default sooner than other firms. Interestingly, none of the macroeconomic variables tested is significant. Hence, macroeconomic conditions are not relevant in explaining the time until default for start-up firms, in contrast to the results obtained when examining the determinants of default probabilities for the full sample.

Finally, in order to complete our analysis, we estimated parametric duration models, using several different distribution functions (namely, exponential, Weibull, Gompertz, lognormal, and log-logistic). The results for one of the es-

[42] Though higher leverage ratios are usually associated with higher default probabilities, as discussed above, in the first years of the firm's life a high level of indebtedness may be required to fund its initial investments, without implying necessarily a higher default probability. Nevertheless, for an older firm, a highly leveraged financial structure, when combined with a deterioration in other financial ratios, may signal increased credit risk, as illustrated in the regressions presented for the full sample.

timated models for the sub-sample of start-up firms are displayed in Table 3.8. The estimated coefficients are broadly robust across the different distribution functions considered and do not differ substantially from those obtained using a Cox proportional hazard model. It should be noted that some of the estimated coefficients are displayed as proportional hazard ratios (PH), whereas others are presented as accelerated failure-time coefficients (AFT). The latter present signs opposite to those obtained with the Cox models because they have a different interpretation. Accelerated failure-time models change the time scale by a factor of $exp(-X_i\beta)$, in a general model. A positive coefficient implies an acceleration of time, which is the same as an increase in the expected waiting time until default. The Akaike information criteria (AIC) suggests that the Weibull and the log-logistic distributions are the ones which provide more accurate results.

Table 3.8 - Parametric survival models for new firms, robust

	Exponential		Weibull		Gompertz	Lognormal	Log-logistic	Cox model
	PH	AFT	PH	AFT	PH	AFT	AFT	
ROA	0.993	0.007	0.989	0.003	0.989	0.004	0.003	0.992
	-2.25	*2.25*	*-2.94*	*2.36*	*-2.96*	*2.34*	*2.34*	*-2.31*
Solvency ratio	1.002	-0.002	1.005	-0.001	1.005	-0.001	-0.001	1.003
	0.71	*-0.71*	*1.22*	*-1.30*	*1.22*	*-0.58*	*-1.25*	*0.78*
Investment rate	0.994	0.006	0.996	0.001	0.996	0.000	0.001	0.994
	-1.04	*1.04*	*-0.72*	*0.78*	*-0.71*	*-0.15*	*0.72*	*-1.02*
Liquidity ratio	0.990	0.010	0.990	0.002	0.989	0.003	0.002	0.990
	-4.06	*4.06*	*-4.04*	*2.93*	*-4.07*	*3.23*	*2.94*	*-4.04*
Constant	-	3.151	-	2.093	-	2.443	2.079	-
		9.59		*13.42*		*11.36*	*13.63*	
Log-likelihood	-261.0	-261.0	-237.6	-237.6	-245.1	-241.3	-237.8	-435.3
No. of observations	3847	3847	3847	3847	3847	3847	3847	3847
No. of subjects	2324	2324	2324	2324	2324	2324	2324	2324
No. of failures	68	68	68	68	68	68	68	68
Time at risk	3847	3847	3847	3847	3847	3847	3847	3847
LR chi2	33.3	33.3	44.2	259.9	42.9	146.8	248.1	34.2
Prob > chi2	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
AIC	542.06	542.06	497.20	497.20	512.15	504.68	497.58	

Note: z-scores in italics. New firms are defined as those created from 1996 onwards. All regressions include year control dummies. The models presented in this table were estimated parametrically, using the exponential, Weibull, Gompertz, log-normal and log-logistic distributions, using robust variance estimates. PH stands for proportional hazard ratios. In this case, an estimated coefficient lower than 1 should be interpreted as contributing to lower default probabilities or, more precisely, to a longer time until default eventually occurs. In turn, AFT stands for accelerated failure-time coefficients. A positive coefficient implies an acceleration of time, which is the same as an increase in the expected waiting time until default. The LR/Wald test evaluates the overall significance of the estimated coefficients. AIC stands for Akaike Information Criteria.

Finally, an additional effort conducted to overcome the left-censoring problem was to gather information from the Central Credit Register on loan defaults observed between 1980 and 1995 for the firms included in the sample. As a result, 226 new defaults were taken into account. Using this new information, we still declare that firms are at risk since their creation date, though now we can observe their failure since 1980. Hence, if a firm defaulted between 1980 and 1995, it will now be excluded from the regressions, given that it failed before entering our observation window. Using this additional information allows to fully overcome the left-censoring problem, given that we can argue that a default that occurred before 1980 will hardly condition the firm's default probability from 1996 onwards. The results using this default history are broadly consistent with those obtained when the full default history was not taken into account. Hence, though we have concluded that firms with previous defaults are more likely to default again in the future, the inclusion of a longer default history does not seem to seriously affect regression results.

3.5 Concluding remarks

This chapter focused on the determinants of credit risk, both at an aggregate and at a firm-specific level. On one hand, we tried to understand how systematic factors, which simultaneously affect all firms, condition the evolution of aggregate default rates. On the other hand, we examined how firms' specific characteristics affect their default probabilities.

We started by exploring the links between credit risk and macroeconomic developments at an aggregate level. The results obtained suggest that there are some important links between credit risk and macroeconomic developments. In fact, these results seem to confirm the hypothesis that in periods of economic growth, which are sometimes accompanied by strong credit growth, there may be some tendency towards excessive risk-taking. However, the imbalances created in such periods only become apparent when economic growth slows down.

After examining the determinants of credit risk at an aggregate level, we focused our attention on an extensive dataset with detailed financial information for more than 30.000 firms, which also includes their loan default record. The results obtained suggest that default probabilities are influenced by several firm-specific characteristics, such as their financial structure, profitability and liquidity, as well as by their recent sales performance or their investment policy. After controlling for the most relevant firm-characteristics, the firm's dimension does not seem to contribute to explain differences in default frequencies, though there are some important differences between economic sectors. Lagged information on the firm's financial situation over a short period also seems to be important in explaining why do some firms default on their loan commitments. Furthermore, the firm's default history should be taken into account in the assessment of its credit risk, given that firms which recorded loan defaults in the recent past seem to display much higher default probabilities than other firms.

Finally, when time-effect controls or macroeconomic variables are taken into account together with the firm-specific information, the results of the models improve considerably. The results obtained allow us to conclude that macroeconomic dynamics have an important additional (and independent) contribution in explaining why do firms default. Hence, even though the determinants of loan default at the micro level are ultimately driven by the firms' specific financial situation, there are important relationships between overall macroeconomic conditions and default rates, which should be assessed from a financial stability perspective.

CHAPTER 4

4 What happens after corporate default? Stylized facts on access to credit

4.1 Introduction

By granting credit, banks play a crucial role in the economy as liquidity providers (Diamond and Dybvig, 1983)[43]. Virtually all loans granted by banks have a positive default probability, which is taken into account by banks in their pricing decisions. In the previous chapter we focused on which factors may lead firms to default. The main contribution to the vast literature on credit risk determinants was related to the analysis of the role of macroeconomic conditions on default probabilities[44]. However, even though this literature expanded a lot during the last decade, there is surprisingly scarce evidence on what happens to firms after they default. In this chapter, we aim to fill this gap in the literature by studying two broad questions: What happens to firms

[43] This chapter is based on joint work with Daniel Dias and Christine Richmond, published as Bonfim, D., D. Dias and C. Richmond (2012), What happens after corporate default? Stylized facts on access to credit, Journal of Banking and Finance, 36(7), 2012, pp. 2007-2025.

[44] For a review of the literature on factors influencing firm default see, for example, Duffie and Singleton (2003) or Saunders and Allen (2002).

post-default? And when are firms able to regain access to financial markets after experiencing an episode of financial distress/ default?

These questions should be interesting in any context, but the increase in bank loan delinquencies and defaults worldwide surrounding the 2008-2009 global financial crisis makes this research even more relevant. How many of these firms will be able to overcome financial distress and regain access to credit? Which factors may be more relevant in this process? Do default characteristics influence the likelihood of regaining access to credit markets? By answering these questions, we hope to provide relevant and timely empirical evidence on this issue. We contribute to the existing literature by establishing a set of stylized facts regarding the trajectory of firms post-default. We focus not only on the duration of financial distress but also on the ability to re-access credit markets.

To answer the questions mentioned above, we use a unique dataset from Portugal, the Central Credit Register (CRC), which covers virtually all bank loans granted to Portuguese firms between 1995 and 2008.[45] This time pe-

[45] We acknowledge that bank credit is not the only source of external financing that is available to Portuguese firms. Nevertheless, and similarly to what happens in the rest of Europe, bank credit is the main source of external financing for Portuguese (and European) firms. According to the results of the ECB "Survey on the access to finance of small and medium-sized enterprises in the euro area" for H2-2009, 70% of Euro area SMEs report using a bank loan, overdraft, or line of credit during the last 6 months, compared to market-based financing (where only 2.2% of SMEs had issued debt or equity securities) and to trade credit (24% of SMEs) (ECB, 2010).

riod captures a full credit cycle with a variety of macroeconomic conditions, including the convergence process to the European Monetary Union and the 2008 financial crisis. The CRC collects information on all loans undertaken by each firm with any financial institution in Portugal. One of its main goals is to support participating credit institutions in the assessment of credit risk. The information shared between banks within the scope of this database should therefore have an important role in reducing the traditional information asymmetry problems between borrowers and lenders.[46]

Our results are organized in two parts: 1) "in default" and 2) "post default" periods. With respect to the "in default" period we find that i) 50% of default episodes last 5 quarters or less and, of these, half are resolved in less than 1 or 2 quarters; ii) at the same time, we also observe that if a default episode is not solved in less than 1 year it can take several years to be cleared; iii) the duration of the default is linked to its severity, that is, the more significant the default, the longer it takes to be resolved; iv) not all bank loan default episodes generate write-offs for the banks: only 31% of default events lead to write-offs; and v) of those loans that lead to a write-off, the average loss for

[46] Jappelli and Pagano (1993, 2006) note that public credit registries have the benefits of: (i) improving banks' knowledge of applicants' characteristics, reducing adverse selection problems; (ii) reducing the "informational rents" that banks could otherwise charge customers; (iii) act as a borrower discipline device; and (iv) eliminate or reduce borrowers' incentives to become "over-indebted", derived from simultaneously borrowing from multiple lenders.

the bank is 34%.

Regarding the "post default" period our results show that i) in the first quarter after exiting default, 59% of firms have access to credit but, of these, less than one quarter are able to increase their bank debt; ii) if a firm is not able to regain access to credit in the first year after exiting default, then the likelihood of obtaining credit at any given moment is less than 1%; iii) the duration of exclusion is strongly related to the severity of the default episode. That is, the larger the amount defaulted on, the larger the written-off amount, or the longer the default period, the longer is the period of exclusion; iv) re-access mostly occurs through banks with whom the firm had ongoing lending relationships before the default was resolved; v) there is a high degree of recidivism: one year after clearing the default, almost 25% of firms default again on their bank loan(s); and vi) firms that are able to exit default during recession periods regain access to credit faster and are less likely to default again.

The rest of the chapter is organized as follows: in Section 4.2 we review some of the relevant literature, focusing primarily on empirical findings, and in Section 4.3 we describe the data. Our main results are analyzed in two separate sections: in Section 4.4 we examine what happens to firms when they are in default, while in Section 4.5 we focus our analysis on what happens to firms after they are no longer classified as being in default. Finally, in Section 4.6 we conclude.

4.2 Related literature

The bulk of empirical research on firm default and recovery after financial distress focuses on publicly traded firms in the United States, with an emphasis on bankruptcy reorganization and liquidation procedures.[47] For instance, Franks and Torous (1989), Platt and Platt (1991), Bandopadhyaya (1994), Helwege (1999), and Denis and Rodgers (2007) all consider samples of publicly traded firms that file for Chapter 11 bankruptcy reorganization to analyze the effect of various regressors on the duration of default. The time in default ranges from 16-32 months on average, but size (measured by liabilities, number of employees, or number of creditors) is an important determinant of the duration of default, with smaller firms exiting sooner (Denis and Rodgers, 2007; Morrison, 2007).

Post default performance of large firms appears to be poor. On average, only 29% of firms in Chapter 11 bankruptcy reorganization successfully reor-

[47] Our literature review focuses on research related to what happens to firms after an episode of financial distress. However, there are also some relevant papers that examine post-distress patterns amongst other borrower types, namely personal bankruptcy (Cohen-Cole et al., 2009 and Han and Li, 2011), commercial real estate loans (Brown et al., 2006) and home mortgages (Adelino et al., 2013 and Haughwout et al., 2009).

ganize each year, but Hotchkiss et al. (2008) note that many of the confirmed reorganizations are, in fact, liquidation plans. Analysis of post-bankruptcy cash flows for 89 firms by Alderson and Betker (1999) corroborates earlier findings by Hotchkiss (1995), LoPucki and Whitford (1993), and Hotchkiss and Mooradian (1997) that operating margins are poor and debt ratios are above industry median levels post-bankruptcy. As a consequence of this performance, recidivism rates are high, with one-quarter to one-third of firms subsequently restructuring their debt within five years of initially emerging from bankruptcy. Acharya et al. (2007) also find that creditor recoveries are significantly lower when the firm in default operates in a distressed industry.

It is clear that the experiences of publicly traded US firms are not representative of the overall universe of US firms, which, on average, have only 20 employees (Axtell, 2001). However, few papers examine small or privately-held firms; Berkowitz and White (2004) is one notable exception. The authors consider how personal bankruptcy procedures affect small firms' access to credit in an environment where unincorporated firms debts are the liabilities of the firm owner. Therefore, if the firm fails, the owner can file for bankruptcy, and business and unsecured personal debts will be discharged. Using variation in personal bankruptcy exemptions across US states, it is found that small businesses are more likely to be denied credit if they are located in states with high homestead exemptions, and if loans are received, the values are smaller, with higher interest rates.

Analysis on firm default and recovery outside of the US is limited, but such analysis is important since bankruptcy and liquidation procedures vary across the world. In general, Claessens and Klapper (2005) find that corporate bankruptcy filing rates are higher in countries with more efficient judicial systems. Davydenko and Franks (2008) find that banks in France, Germany, and the UK significantly adjust their lending and reorganization to the national bankruptcy code, in response to different degrees of creditor protection. At the time of loan origination, collateral requirements will directly reflect a bank's ability to realize assets upon default. As a result, adjustments by banks will be able to reduce, but not fully eliminate, the effect of the bankruptcy code on default outcomes.

Evidence on the duration and severity of defaults by firms outside the US is also scarce. Franks and Sussman (2005) consider a sample of 542 small- and medium-sized financially distressed UK firms that are transferred to their bank's workout unit, finding that, on average, these firms spend 7.5 months in the bank's workout unit and 60% of firms in the sample operate as going concerns. Secured creditors in the country fare well within the formal corporate bankruptcy regime and 75% of small firms that default subsequently enter formal bankruptcy receivership, while average bank recovery rates are 75%, as firm assets are pledged as collateral to banks in most cases. In a study of Sweden's auction bankruptcy system for small firms, Thorburn (2000) finds that three-quarters of firms are auctioned as going concerns, and the direct costs average 6.4% of pre-filing value of assets, suggesting that it is an efficient restructuring mechanism for small firms. In Portugal, Antunes (2005) finds that the severity of default influences the probability of liquidation, but that the number of employees is the largest determinant of the time profile of the liquidation/ recovery process.[48]

Finally, another important dimension of the costs of corporate default are the losses incurred directly (and indirectly) by banks. The implementation of Basel II contributed to some expansion of the literature on recovery rates and loss given default (LGD). Some examples are Altman et al. (2005), Carvalho and Dermine (2006), Bruche and González-Aguado (2010), and Bastos (2010).

All in all, most of the existing literature on corporate default and recovery after financial distress focuses on US publicly traded firms. Evidence on small and medium enterprises, especially outside the US, is also relatively scarce. Moreover, most of this literature focuses on bankruptcy, liquidation and re-organization procedures. Our work makes a contribution to fill both of these

[48] In Appendix 1 we compare the bankruptcy codes of Portugal and the US.

gaps in the literature: we analyze the entire universe of firms with access to bank loans in a European country; and we focus on a broader event related to financial distress, corporate loan default.

4.3 Data

The main data source for this chapter is the Central Credit Register (CRC) database of the Banco de Portugal. Portuguese law mandates that all financial institutions operating in Portugal report, on a monthly basis, to the Banco de Portugal all loans above 50 euros and all this information is kept in the CRC database. In addition to the information on the amounts, this database also has information on other loan characteristics. It is possible to know if the loan is a joint or single liability, or if it is an off-balance sheet item (such as the undrawn amount of a credit line or a credit card). More importantly for the purposes of our study, the database includes information on loan defaults and renegotiations. All financial institutions operating in Portugal are obliged to report data to the CRC and are allowed to consult information on their current and prospective borrowers, with their consent. As a result, when granting a new loan, a bank can easily observe whether the applicant has any amount of credit overdue at that moment, as well as the total amount borrowed from different banks.

Using information contained in the CRC between 1995 and 2008, we identify all firms that record at least one episode of default during this period.[49] In the CRC, a default can be classified as a loan with late repayment (coded as Type 7 in the database) or as a liability involving litigation (coded as Type 8).[50] We consider that there is a default only when a firm has a loan recorded in either of these two categories for an entire quarter. This avoids mining the data with very short-lived episodes, which are most likely caused by reporting errors or problems with bank transfers.[51]

A default is recorded by a bank in the Credit Register whenever a firm has overdue principal or interest for more than 90 days. It should be noted that a default is usually driven by a firm's decision: facing liquidity constraints, the firm finds itself in a situation in which it cannot honor its commitments and chooses to default on a loan with a given bank (or with several). It is also possible that the firm defaults for strategic reasons (Bolton and Scharfstein, 1990, 1996). Nevertheless, when a firm is in financial distress, the bank may

[49] We exclude unincorporated businesses from this analysis, as their assets are not autonomous from those of the owner. For statistical purposes, these businesses are usually classified as households.

[50] The borrowers may be in arrears in relation to the principal and/or interest and other costs. For the principal, there is a default if at least 30 days have elapsed from the due date. For interest and other costs, there is a default from the date on which payments should have been made.

[51] We do not include loan write-offs in the definition of default, even though this information is also available in the CRC. This choice is motivated by the fact that when a bank writes-off a loan from its books it is implicitly assuming that the probability of repayment is very small, though still positive.

avoid forcing the firm to default if, for example, the loan is renegotiated or restructured.

Our unit of observation is a firm-quarter pair. Using quarterly data for the period 1995-2008, there are more than 1 million default observations, referring to 165,165 different default episodes in more than 100,000 firms.[52] We consider that a firm emerges from default when it does not record a default on bank loans in a given quarter, but was in default during the entire previous quarter. This may mean that the firm is observed in the CRC but with no records referring to outstanding defaults, or that the firm is no longer present in the CRC. This latter possibility may imply that the firm closed or that it continues to operate but without access to bank credit.

The amount and quality of the information available are superior to that used in most papers focusing on default recoveries, which usually analyze only a limited set of publicly traded firms, thus allowing us to conduct a richer analysis.[53]

[52] We do not have information strictly on a loan-by-loan basis, as banks report information for each borrower aggregated by loan type.

[53] In Portugal there are less than 100 publicly traded companies, while in 2008 there were more than 350,000 firms operating in the country. This number highlights how partial and incomplete the results would be if our study focused only on the set of publicly traded companies.

4.4 What happens while firms are in default?

During the last decade, the literature on the determinants of firm default increased dramatically, in part driven by the discussion and subsequent implementation of Basel II. However, much less attention has been devoted to the dynamics of the default process itself and, more importantly, to what happens to firms after they fail to comply with their debt obligations. In this section we explore the richness of the information contained in the CRC database to analyze in detail the evolution of default episodes, from their onset until their resolution. In Section 4.5 we proceed with our analysis by focusing on what happens to firms after the default episode is considered resolved.

In general, a corporate default episode can be characterized by three elements: 1) incidence and amount of the default; 2) the length of the default event; and 3) the losses ultimately faced by the financial institution. Better understanding these three elements is of great interest because they have a direct impact on how financial institutions manage their risk exposure and how regulatory agencies design their policies. Below, we analyze each of these elements.

4.4.1 Default incidence and amounts

The first question we address is how the default incidence and the corresponding amounts evolved in Portugal during the sample period, 1995 to 2008. In Table 4.1 we present various statistics regarding the amounts and the incidence of bank loan defaults over time.

Table 4.1 - Firms in default: some characteristics

	Number of firms with a loan	Average amount outstanding	Number of new firms with a loan	Number of firms in default	Percentage of firms in default	Amount in default	Credit overdue ratios for firms in default		New episodes of default		
	Number	Mean (euros)	Number	Number	%	Mean (euros)	As a % of total credit	As a % of total credit inc. off-balance sheet	Number	Average amount (euros)	As a % of the number of firms with a loan (default rate)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1995	126,590	384,566	29,153	17,719	14.0	190,124	72.1	69.8	5,543	45,741	4.4
1996	138,471	382,397	24,530	18,353	13.3	188,366	74.7	72.4	6,634	64,970	4.8
1997	149,890	401,970	23,981	19,221	12.8	159,071	74.4	72.0	7,086	47,246	4.7
1998	164,463	425,245	26,560	18,854	11.5	147,865	74.0	71.6	6,000	42,107	3.6
1999	183,340	478,633	28,085	17,531	9.6	142,006	72.5	69.8	7,454	41,767	4.1
2000	202,693	534,377	27,440	19,485	9.6	118,813	69.6	67.1	8,213	24,165	4.1
2001	227,642	546,375	33,979	24,880	10.9	108,053	61.5	59.6	11,997	31,827	5.3
2002	253,211	568,362	35,010	29,122	11.5	98,057	59.2	56.8	15,522	32,089	6.1
2003	262,423	544,646	26,312	31,522	12.0	92,733	58.2	55.7	14,578	22,903	5.6
2004	272,855	523,897	24,253	33,322	12.2	83,908	59.9	57.2	13,353	24,502	4.9
2005	279,364	535,183	22,987	33,189	11.9	75,962	62.7	59.8	12,903	29,974	4.6
2006	288,852	556,805	25,633	34,440	11.9	73,246	60.6	57.9	14,983	22,058	5.2
2007	300,161	575,760	28,496	40,198	13.4	66,348	60.0	57.3	20,629	24,615	6.9
2008	307,840	608,527	25,442	45,120	14.7	74,241	60.5	57.8	20,270	35,721	6.6
Total	479,298	525,118	381,861	108,479	12.1	105,142	64.1	61.5	165,165	31,919	5.2

Notes: Default is defined as the sum of liabilities with late repayments and of loans in litigation. We consider that there is a default only when a firm records a loan in any of these two categories for an entire quarter. Column (1) refers to the total number of firms with a loan, in each quarter and column (2) shows the average amount outstanding of each firm. Column (3) presents the number of new firms with a loan in each quarter, defined as firms that were not observed in the CRC previously, during the sample period. The firms that were borrowing in 1995Q1 are not considered as new firms in 1995. Column (4) refers to the number of firms that, in each quarter, record any amount in default. Column (5) presents the percentage of firms in default, computed as the ratio between the number of firms in default (column 4) and the total number of firms with a loan (column 1), in each quarter. The percentage for the total is the weighted average for the whole sample period. Column (6) refers to the average amount in default during the quarter. In column (7), the credit overdue ratio is defined as the sum of loans in late repayment and in litigation at the end of each quarter, as a percentage of total credit granted to that firm. In column (8) this definition is extended to include off-balance sheet liabilities in the denominator of this ratio (these include the unused amounts of credit lines, for instance). The new episodes of default reported in columns (9), (10) and (11) refer to defaults recorded by firms without any default in the previous quarter. We exclude firms that were in default in 1995Q1. In column (11) we present the number of new default episodes as a percentage of the number of firms with a loan (column 1), i.e., the default rate.

Several interesting results arise from the analysis of this table. First, during our sample period there was a substantial expansion of credit to firms in Portugal, as shown by the significant increase in the number of firms with access to loans (column 1). As discussed in Antão et al. (2009), the liberalization of the Portuguese financial system in the late 1980s and early 1990s created the conditions for an expansion of credit granted to the private sector. This growth was fuelled by the significant decrease in bank lending interest rates during the 1990s as the economy gradually converged to meet the euro accession criteria. The participation in the euro area improved the funding conditions of Portuguese banks in international wholesale markets, with virtually no exchange rate risk, thus further contributing to improve the access of Portuguese non-financial firms to bank loans. Against this background, loans granted to non-financial firms increased by an average annual rate of 12% during these years, reflecting not only an increase in the amount of loans granted to each firm (column 2), but also an increase in the number of firms with access to credit (column 3). In fact, around 80% of the firms analyzed started to have access to credit after 1995Q1.

Second, at the same time credit expanded in Portugal, the incidence of non-performing loans had a U-shaped path (column 5). Between 1995 and 2000 there was a significant decrease (from 14% to 9.6%), but between 2000 and

2008 this rate increased almost every year and reached a higher level than what was experienced in 1995. Although the default incidence had a U-shaped path, the default rate had an upward trend, most notably from 2001 onwards, with the period average equal to 5.2% (column 11).[54] Default rates peaked in 2002, possibly reflecting the increase in interest rates and the marked slowdown of economic activity after 2000. Most of these new defaults correspond to smaller firms, as shown by the evolution of amounts in default (column 10). Hence, despite the increase in default frequencies, its aggregate magnitude decreased during most of the sample period (see Antão et al., 2009).

Third, the average amounts involved in the default episode decreased initially – from 1995 to 2000/2001 – and remained fairly constant for the rest of the period. For the entire period the average amount in default is 105,142 euros (column 6). On average, at the beginning of a default episode, the amount overdue is 31,919 euros (column 10). The decrease of the amounts in default during the sample period does not necessarily suggest that defaults became less severe, as the average firm size in the sample also decreased over time. Therefore, to better evaluate how the severity of default evolves during the sample period, in columns (7) and (8) we present the credit overdue ratio

[54] These two variables, default incidence and default rate, have different paths because during the sample period the duration of the "in default" period was not constant.

for firms in default (the latter column includes off-balance sheet liabilities).[55] This ratio stands, on average, at 64 % (62% if off-balance sheet liabilities are included), having decreased steadily during the first half of the time period under analysis. Therefore, even though defaults became more frequent, their size and severity decreased simultaneously during our sample period.

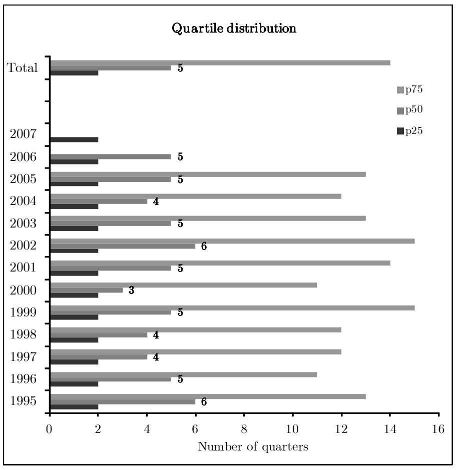
In sum, during the period 1995-2008, Portugal experienced a rapid expansion of credit to firms. In the first half of this period (1995-2000/2001), there was a steady decrease in the incidence rate of non-performing loans, but in the second half of the period it increased to values similar to those observed in 1995. The default rate had a more volatile behavior, mirroring to some extent overall economic conditions. The year of 2007 marked the beginning of the tensions in global financial markets and, not surprisingly, we observe that since then there has been an increase in the default incidence rate, as well as an increase of the average amount in default. However, the credit overdue ratios in 2007 and 2008 are not very different from previous years. As these ratios are defined as the amount of credit overdue as a percentage of total outstanding loans, the increase of the average amount in default suggests that firms in default during this more recent period are slightly larger than before.

[55] These off-balance sheet liabilities include, for example, the undrawn amount of credit lines.

4.4.2 Time in default

The second aspect of the "in default" period we consider is its length. That is, after a firm is declared to be in default to a bank, how long does it take until a bank declares that the firm is no longer in default? Figure 4.1 shows how the default duration evolved over time.

Figure 4.1: Number of quarters in default



From Figure 4.1 we see that the default duration is not extremely long. Overall, more than 50% of firms exit default in 5 quarters or less and more than 25% of firms exit default in 2 quarters or less. Over time, the median duration does not vary significantly, ranging between 3 and 6 quarters. The first quartile of the distribution of default durations remains unchanged during the full period. Regarding the rest of the distribution, the story is somewhat different. In particular, the 25% longest default spells are longer than 14 quarters and during the sample period this number oscillates between 11 and 15 quarters.

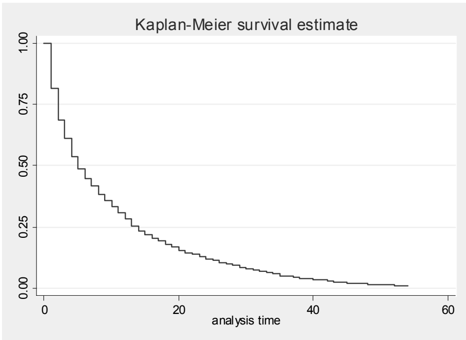
If severity and length of the default episodes are positively correlated, then it seems that over time the importance of the least problematic events did not change much. We reach this conclusion because we see that the first quartile of the default duration distribution is fairly stable throughout the sample period. On the other hand, from the variability of the third quartile of the default distribution, it seems that the importance of the more severe cases oscillated significantly during the sample period.

To complement the results in Figure 4.1, we present estimates of the survival and hazard functions for the "in default" period (Figures 4.2 and 4.3).[56]

From these figures, two important results emerge. First, default spells can be very long. Even though the third quartile of the distribution is less than

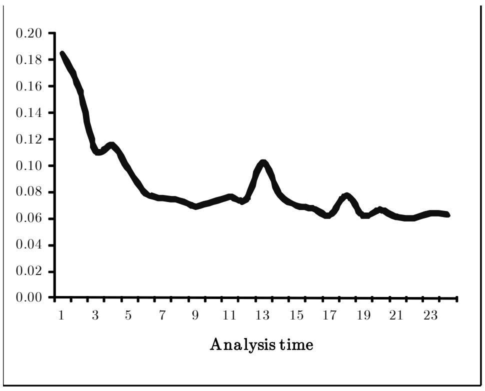
[56] The survival function is defined as the probability of remaining in default until t: $S(t) = \Pr(T \geq t) = 1 - F(t)$. The hazard function is defined as the probability of a firm leaving default in the time interval $[t, t + dt)$, conditional on being in default: $h(t) = \lim \frac{\Pr(t \leq T \leq t+dt | T \geq t)}{dt}$, $dt \to 0$. T denotes the time a firm remains in default.

Figure 4.2: Default duration



Note: Analysis time defined as quarters since the beginning of the first default episode. The survivor estimate is defined as the probability of remaining in default until t: S(t)=Prob(T>=t)=1 - F(t).

Figure 4.3: Hazard function for the time in default



Note: Analysis time defined as quarters since the beginning of the first default episode. The hazard function is defined as the probability of a firm leaving default in the time interval [t $t+dt$), conditional on being in default: h(t) = lim Prob($t<=T<t+dt$ | $T>=t$)/dt, as dt->0. In the figure, the hazard is censored at 24 quarters, covering 95% of all observations.

14 quarters, more than 10% of episodes last more than 24 quarters (6 years). This result is visible in the survival function (Figure 4.2). Second, the exit rate of default drops sharply in the first 2 years, from around 20% to slightly more than 6%. This is important because it suggests that when a default episode is not resolved within the first four to six quarters, then it takes substantially longer to be resolved.

An interesting question is how the default amounts evolve as default duration increases. Tables 4.2A and 4.2B shed light on this question.

Table 4.2A - Evolution of the firms' situation since the beginning of the default episode

	Number of observations	**Amount of credit overdue** (euros)		**Credit overdue ratio** (%)		**Amount of total credit outstanding** (euros)		**Number of bank relationships**		**Number of relationships in default**		**Number of bank relations in default (as a % of the total number of relationships)**	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Firms in default for: (in quarters)													
1	165,165	31,919	2,870	37.9	13.9	375,300	30,170	2.47	2.0	1.3	1.0	68.9	66.7
2	110,208	48,675	5,000	49.9	36.9	327,402	26,302	2.37	2.0	1.4	1.0	75.2	100.0
3	86,674	63,107	7,071	58.4	67.3	315,105	24,890	2.32	2.0	1.5	1.0	79.2	100.0
4	70,016	77,239	9,510	64.4	88.4	307,386	25,115	2.31	2.0	1.6	1.0	82.0	100.0
5	60,348	87,083	11,220	69.5	98.9	296,448	24,753	2.28	2.0	1.7	1.0	84.3	100.0
6	50,377	96,381	12,450	72.8	100.0	332,136	24,773	2.29	2.0	1.8	1.0	85.9	100.0
7	42,618	106,597	14,690	75.4	100.0	291,051	26,115	2.31	2.0	1.8	1.0	87.1	100.0

Notes: In this table are depicted firm and loan characteristics for firms that have been in default for 1 quarter (line 1), 2 quarters (line 2), etc., up to 7 quarters. In each line, the variables refer to the situation in the x quarter after the default episode began. The number of bank relationships is computed as the number of loans obtained from different financial institutions (including non-monetary financial institutions).

Table 4.2B - Firm and loan characteristics for default episodes with different total durations

	Number of observations	**Amount of credit overdue at start of default** (euros)		**Credit overdue ratio at start of default** (%)		**Total amount of credit outstanding at start of default** (euros)		**Number of bank relationships at start of default**		**Number of bank relationships in default at start of default**		**Number of bank relations in default (as a % of the total number of relationships) at start of default**	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Total duration of default (in quarters)													
1	54,957	20,958	1,730	26.8	6.6	472,415	34,890	2.6	2.0	1.1	1.0	62.3	50.0
2	23,534	24,666	2,290	33.9	10.8	316,803	28,031	2.4	2.0	1.2	1.0	68.1	60.0
3	16,658	27,249	2,340	43.7	20.0	297,521	19,105	2.2	2.0	1.2	1.0	73.3	100.0
4	9,668	32,193	2,860	40.8	17.5	288,447	24,530	2.2	2.0	1.2	1.0	72.9	100.0
5	9,971	39,706	4,228	53.5	49.0	231,072	21,803	2.1	2.0	1.4	1.0	78.8	100.0
6	7,759	23,755	2,610	54.9	56.1	623,269	14,020	2.0	2.0	1.3	1.0	79.4	100.0
7	5,591	36,689	4,190	50.2	34.9	249,616	21,760	2.2	2.0	1.4	1.0	76.9	100.0
8	4,112	43,909	4,110	46.3	27.2	239,700	26,640	2.2	2.0	1.4	1.0	74.7	100.0

Notes: In this table are depicted firm and loan characteristics for firms with different total durations of default (between 1 and 8 quarters). In each line, the variables refer to the situation at the beginning of the default episode, for firms which default episodes lasted for x quarters. The number of bank relationships is computed as the number of loans obtained from different financial institutions (including non-monetary financial institutions).

In these two tables we examine two different perspectives on default duration. First, in Table 4.2A we show what happens to the amounts in default, the credit overdue ratio and the number of bank relationships as the length of the default period increases. Second, in Table 4.2B we present the same statistics but in this case at the start of the default event, for firms with different default durations. More specifically, in Table 4.2A each row refers to the *current* default duration of each firm (firms that have been in default for 1 quarter, 2 quarters, etc., up to 7 quarters), whereas in Table 4.2B each line refers to firms with different *total* default durations (i.e., firms that recorded a default episode that lasted for 1 quarter, 2 quarters, etc., up to 8 quarters).

The joint analysis of these two tables indicates two important results: 1) as the default duration increases the situation worsens; and 2) the firms that stay longer in default are those with worse initial conditions, compared to firms that exit faster. Regarding the worsening of the situation (Table 4.2A), there is a component that is somewhat mechanic, that is, the amounts overdue automatically accumulate every period. Besides this accumulation effect, there is also a true worsening of the situation. The amounts overdue and the credit overdue ratio increase significantly with each quarter in default. Moreover, the percentage of bank relationships on which the firm defaults also increases with default duration (firms in default borrow, on average, from more than 2 different banks).

Regarding the conditions firms enter default with (Table 4.2B), we see that the credit overdue ratios at the start of the event are larger for firms that ended up staying longer in default – this is visible in columns (4) and (5). Also, the total amount outstanding at the start of the default episode is, on average, larger for firms with shorter default episodes, thus suggesting that larger firms are able to leave default earlier (columns 6 and 7).

From the analysis of the default period, we conclude that the longer a firm stays in default the more complicated its situation becomes. Another important finding is that firms that stay longer in default are also firms whose conditions at the start of the default are worse.

4.4.3 Losses incurred by banks

The final aspect of the default period we analyze relates to the losses generated by the default, that is, how costly can a default episode be for bank lenders. In our dataset, we only observe one component of this cost: the amounts that banks declare as write-offs. In order to have a better measure of the costs of default for banks we would need information on legal and processing costs, as well as on collateral and guarantees that mitigate the losses. Despite the caveats of our measure of loss estimates, we still find it sufficiently interesting and informative. Table 4.3 shows the evolution of bank losses due to loan write-offs over time.

Table 4.3 - Estimates of losses incurred by the banks

	Bank losses due to written-off loans: including all loans					Bank losses due to written-off loans: only including events that originated a write-off					Bank losses due to written-off loans: including all loans whose default was longer than 1 year			
	N	mean	p50	p75	p99	N	mean	p1	p50	p99	N	mean	p50	p99
		%	%	%	%		%	%	%	%		%	%	%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1995	5,880	2.6	0.0	0.0	86.2	553	28.0	0.01	9.4	99.6	3,861	3.2	0.0	88.9
1996	6,229	6.9	0.0	0.0	97.0	1,235	34.7	0.04	19.4	99.9	3,851	8.9	0.0	98.7
1997	6,778	4.8	0.0	0.0	93.3	1,238	26.0	0.02	10.1	99.7	3,925	6.3	0.0	96.6
1998	8,626	8.7	0.0	0.0	99.3	1,805	41.8	0.00	35.0	100.0	5,889	11.5	0.0	99.8
1999	6,042	9.1	0.0	0.0	99.6	1,215	45.3	0.03	38.1	100.0	3,675	14.4	0.0	99.9
2000	6,382	8.5	0.0	0.0	98.9	1,354	40.1	0.02	26.8	99.9	3,501	12.9	0.0	99.5
2001	10,614	9.8	0.0	0.6	99.9	3,397	30.6	0.00	6.5	100.0	4,906	17.6	0.0	100.0
2002	12,234	9.8	0.0	0.7	99.0	3,840	31.2	0.00	8.6	99.9	6,220	17.8	0.0	99.8
2003	11,956	8.4	0.0	0.4	99.3	3,735	27.0	0.00	4.5	99.9	5,655	15.8	0.0	99.8
2004	13,163	11.1	0.0	1.5	99.7	4,627	31.7	0.00	8.0	100.0	6,740	19.2	0.0	99.8
2005	13,662	14.6	0.0	2.9	99.9	5,030	39.7	0.00	17.4	100.0	7,000	26.1	0.0	100.0
2006	14,636	15.4	0.0	4.5	99.9	5,761	39.0	0.00	18.3	100.0	7,230	29.0	1.5	100.0
2007	15,166	11.5	0.0	2.6	99.5	5,686	30.7	0.00	8.4	99.9	5,713	27.8	4.2	99.9
2008	12,945	11.2	0.0	3.1	99.6	4,828	30.1	0.01	10.3	99.9	5,327	25.1	4.2	99.9
Total	144,313	10.3	0.0	0.8	99.7	44,304	33.7	0.00	11.1	100.0	73,493	18.2	0.0	99.9

Notes: Estimates of losses incurred by the banks are based on write-offs and write-downs reported by banks to the Central Credit Register. These losses do not include recovery costs and do not consider collateral. Losses are displayed as a percentage of total loans outstanding after the default episode ends (i.e., once the firm does not record late repayments or loans in litigation in the end of the following quarter). As in previous tables, observations refer to pairs firm-quarters, which means that these loss estimates do not refer to a specific loan or bank, but to all outstanding credit liabilities of the firm. We exclude all observations in 2008Q4, the last quarter in the sample, given that these refer to situations still unfolding.

In this table we present two main statistics regarding bank losses due to loan write-offs. The first is the unconditional loss, that is, given all default episodes, what is the average loss incurred by the bank (columns (1)-(5)). In this case we find that, on average, any given default will generate a loss due to write-offs of 10.3% of the total amount outstanding at the time the default episode ends. This figure is much lower than the 45% loss given default rate considered for corporate uncollateralized loans in the foundation approach of Basel II. However, as we do not have information on collateral or legal costs, this comparison is not clear-cut.

The second statistic is the conditional loss, that is, given all default episodes that lead to a write-off, what is the average loss incurred by the bank (columns (6)-(10)). In this case, the figure is substantially higher, 33.7%, but this large difference comes mainly from the fact that most default episodes do not lead to any write-off (only 30% of default events generate a write-off for the bank).[57]

Another interesting result is that, over time, the average unconditional loss has increased gradually (from 3% to 11%), whereas the average conditional loss has varied significantly during the sample period (between 26% and 45%). It should be noted that, to a large extent, the increase in the number of loan write-offs over time reflects a mechanical accumulation process, as some banks keep loans classified in this category for a long period.

A final result relates to the duration of the default event and the inflicted loss. In the last 4 columns of Table 4.3 we show that for loans in default for

[57] The percentage of default events is the ratio between the values in columns (6) and (1) from Table 3.

more than 1 year, the unconditional loss almost doubles (18.2% vs. 10.3%).

4.5 What happens after exiting default?

A second question we address in this chapter is what happens to a firm after leaving default. In particular, we are interested in knowing if firms are able to borrow again, and if so, how long it takes for this to happen; when a firm is able to borrow again does it borrow from the same lender or from a different lender; and finally, do firms tend to default again or not?

In Table 4.4 we provide a broad picture with respect to some of these questions.

Table 4.4 - After leaving default

	Number of default episodes resolved	Default episodes resolved as a % of defaults in each year	Number of default episodes resolved (only first defaults)	Firms that continue in the credit register in the quarter after their first default ends		Firms that record a new default episode in the 3 years after exiting default		Firms that are not in the CRC in the 3 years after exiting default	
				Number	% of total	Number	% of total	Number	% of total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1995	5,880	10.6	2,222	1,764	79.4	1,223	55.0	225	10.1
1996	6,229	10.6	3,769	2,624	69.6	2,075	55.1	492	13.1
1997	6,778	11.4	3,847	2,785	72.4	1,722	44.8	580	15.1
1998	8,626	14.8	4,978	3,190	64.1	2,586	51.9	477	9.6
1999	6,042	11.2	3,491	2,793	80.0	1,597	45.7	389	11.1
2000	6,382	11.2	3,704	3,036	82.0	1,944	52.5	300	8.1
2001	10,614	15.5	6,976	5,827	83.5	3,564	51.1	418	6.0
2002	12,234	14.7	6,997	5,985	85.5	3,436	49.1	594	8.5
2003	11,956	12.9	7,014	6,037	86.1	3,472	49.5	655	9.3
2004	13,163	13.8	7,578	6,660	87.9	3,202	42.3	694	9.2
2005	13,662	13.5	7,433	6,359	85.6	3,204	43.1	778	10.5
2006	14,636	14.7	7,942	6,861	86.4	-	-	-	-
2007	15,166	13.6	8,860	7,201	81.3	-	-	-	-
2008	12,945	10.0	7,668	6,059	79.0	-	-	-	-
Total	144,313	12.8	82,479	67,181	81.5	28,025	48.3	5602	9.7

	1 quarter after first default episode ends									
	In credit register								Not in credit register	
	Firms with more access and without problem loans		Firms with access (but less than before)		Firms with access but still with written-off loans		Firms only with written-off loans (no access)		Without access or closed	
	Number	% of total	Number	% of total	Number	% of total	Number	% of total	Number	% of total
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1995	330	20.5	780	48.4	27	1.7	17	1.1	458	28.4
1996	641	16.5	1,748	44.9	313	8.0	49	1.3	1,145	29.4
1997	604	16.5	1,692	46.2	176	4.8	130	3.5	1,062	29.0
1998	538	11.6	1,701	36.7	209	4.5	396	8.5	1,788	38.6
1999	761	20.0	1,533	40.2	367	9.6	451	11.8	698	18.3
2000	545	15.3	1,624	45.6	238	6.7	487	13.7	668	18.8
2001	1,189	18.2	3,149	48.2	582	8.9	462	7.1	1,149	17.6
2002	1,091	16.2	3,713	55.0	471	7.0	466	6.9	1,012	15.0
2003	957	13.4	3,950	55.3	528	7.4	735	10.3	977	13.7
2004	752	9.8	3,674	48.0	873	11.4	1,438	18.8	918	12.0
2005	577	8.6	3,274	49.0	685	10.2	1,076	16.1	1,074	16.1
2006	662	7.9	3,149	37.4	1,185	14.1	2,352	27.9	1,081	12.8
2007	985	11.5	3,800	44.4	676	7.9	1,442	16.8	1,659	19.4
2008	920	9.6	4,235	44.4	1,025	10.7	1,751	18.4	1,609	16.9
Total	10,552	12.8	38,022	46.1	7,355	8.9	11,252	13.6	15,298	18.5

Notes: A default episode is considered resolved if there is no record of loans with late repayments or in litigation in the end of the following quarter. We exclude firms that were in default in 2008Q4, the last quarter in the sample. The definition of first defaults only takes into account information since 1995. Column (2) considers the number of default episodes terminated as a % of the number of observations in default. In columns (6) to (9) there is no information for the last 3 years given that a 3 year window is used. After default, firms can either continue to be observed in the credit register (columns 4 and 10-17) or they can cease to appear in the CRC (column 18). In the latter case firms can have either ceased to operate or they can still be in operation but without having access to loans from financial institutions. By construction, there are no firms in default in the quarter after the default episode ended. Firms with more access are those with more outstanding bank loans (including credit lines) than at the end of the default episode and without any record of default or write-offs. Firms with less access than before are those which have the same or less loans outstanding that at the end of the default episode.

The first three columns of Table 4.4 show the number of default episodes that are resolved every year. Even though this number increased substantially during the sample period, the "exit rate" from default was relatively stable during the same timeframe.[58] To compute these numbers (the number of default episodes resolved and the default "exit rate"), we count all firms that were in default in period $t-1$ and were not in period t, taking into account only the first default episode of each firm during the sample period.

Once a firm leaves default, there are two main possibilities: either the firm continues to be present in the Credit Register in the quarter after the first default episode has been resolved (column 4); or it ceases to be reported by banks (column 18). In the latter case, the lack of presence in the CRC may reflect the fact that the firm ceased to operate. However, it is also possible that firms survive without having access to bank loans. A rough estimate suggests that at least 12% of the firms that disappear from the CRC after default are still operating afterwards. This may either reflect an inability to regain access to bank credit after default or, alternatively, it may be a decision made by the firms, which may prefer to use internal funds or trade credit to finance themselves. These effects are not easily disentangled.[59]

[58] In 2008 the value is substantially lower than for the other years because the last quarter of 2008 was excluded from the analysis.

[59] This estimate was conducted by searching for the firms that are not in the CRC in the 3 years after default (column 8) in another dataset, *Quadros de Pessoal*. This database covers

One of the most surprising results we obtain when analyzing post-default behavior is that almost half of the firms that resolve their first default episode record at least one more default episode in the following 3 years (column 7). The intensity of this recidivist behavior is impressive, especially taking into account that information on loan defaults is shared between banks using the CRC.[60] It appears that banks are generally willing to continue to grant loans to firms after they resolve an episode of financial distress, despite facing remarkably high default probabilities. From this data we cannot tell whether recidivism is caused by financial (inability to borrow) or by economic (insolvency) problems. If financial problems are the main reason, then there is mutual interest of the lender and the borrower to overcome the problems that may be originating the default, whereas if the problems are economic then it should be optimal to not lend to the firm.[61]

We can distinguish between two types of re-access: i) simple access (sum-

all Portuguese firms with more than 10 employees. Hence, the estimate presented is a lower bound for the number of firms that no longer have access to credit markets after default. From the 5602 firms that cannot be found in the CRC in the 3 years after the default is cleared (considering only defaults resolved until 2006), at least 686 firms are found to still be operating, but without having access to bank loans. Given this, the maximum bankruptcy or liquidation rate after default is around 8%, thus showing that most firms are able to overcome a default episode.

[60] It should be noted that the history of past default episodes is not available to banks participating in the CRC, who can only observe whether firms are currently in default.

[61] Adelino et al. (2009) and Haughwout et al. (2009) find evidence of significant recidivism problems in mortgages (the latter paper focuses on subprime loans). In both papers, the authors examine the interaction between renegotiation and the incentives for repeated defaults.

ming up columns 10 and 12); and ii) increased access (considering only column 10). In the former case, we consider that the firm regains access simply if it continues to have access to any bank loans after the default is cleared (we refer to this definition as "broad access").[62] In the latter, we consider a stricter access definition and take into account only those cases in which the firm had access to a new loan after default ("strict access"). Since we do not have information on a loan-by-loan basis, we consider all cases in which the total amount outstanding is larger than that observed when the default ended.[63]

Focusing on what happens in the quarter immediately after the firms' first default episode is resolved, we observe that access rates depend crucially on the access definition we use. In the case of strict access, only 13% of firms were able to increase their bank credit in the first quarter after default. With respect to the broad access definition, 59% of firms had access to credit in the first quarter after resolving the default.[64] Hence, most firms do not face a long exclusion from credit markets as a penalty for their past defaults. Over time these two statistics have different paths. While in the case of strict access there is a fairly monotone decrease, in the case of broad access there is some

[62] In fact, most firms never lose access to credit completely while they are in default, as firms usually default only on part of their total outstanding commitments.

[63] Given that a significant portion of loans to firms have short maturities, a firm may have had access to a new loan (or loan renewal) even if the total outstanding amount did not increase. This access definition may then be too strict, thus justifying the need to consider the two alternative definitions.

[64] The 59% figure is the sum of the last row of columns (11) and (13) from Table 4.

volatility during the sample period: instantaneous access rates decreased until 1998, but peaked in 2002. Afterwards, there was a gradual decrease.

We consider two additional possible outcomes after default: firms that have access to loans but still record some written-off loans (9%) and firms only with written-off loans, that is, no access (14%). These two outcomes lie somewhere between default and access. On one hand, these firms are not technically in default. On the other hand, we cannot consider that the problems generated by the default event are fully overcome.

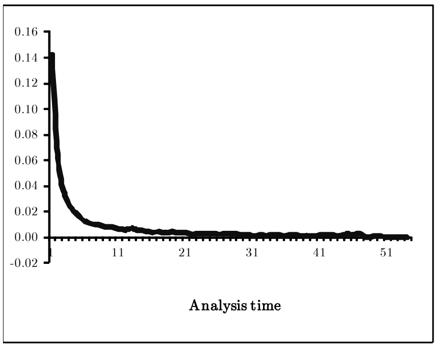
4.5.1 Duration of exclusion

Above we provided some information regarding the process of regaining access to credit after a default is cleared. In this subsection, we expand on the previous results by analyzing more aspects of the process. To start, we show non-parametric estimates of the survival and hazard functions of the time it takes for a firm to borrow again.[65] These results refer to the two definitions of access discussed previously, that is, the ability to borrow more money than before (strict definition) and the ability to keep having some loans (broad definition). Figures 4.4 and 4.5 refer to the former, while Figures 4.6 and 4.7

[65] The survival function is defined as the probability of regaining access to credit until t: $S(t) = \Pr(T \geq t) = 1 - F(t)$. The hazard function is defined as the probability of a firm leaving the exclusion state in the time interval $[t, t+dt)$, conditional on being excluded from credit markets after the default is cleared: $h(t) = \lim \frac{\Pr(t \leq T \leq t+dt|T \geq t)}{dt}, dt \to 0$. T denotes the time a firm remains excluded from access to credit after default.

refer to the latter.

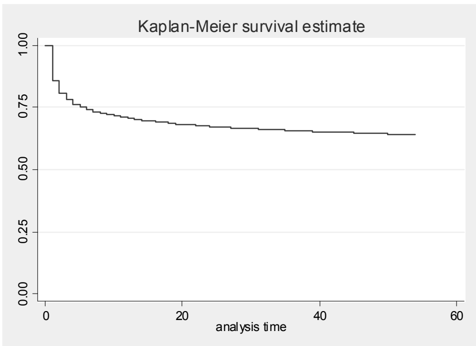
Figure 4.4: Hazard function for time until more access



Note: Analysis time defined as quarters since the end of the first default episode. The hazard function is defined as the probability of regaining access to credit in the time interval [t, t+dt), conditional on not being in default: h(t) = lim Prob(t<=T<t+dt | T>=t)/dt, as dt->0. More access is defined as having a larger amount of outstanding bank loans (including credit lines) than at the end of the default episode and not having any record of default or write-offs.

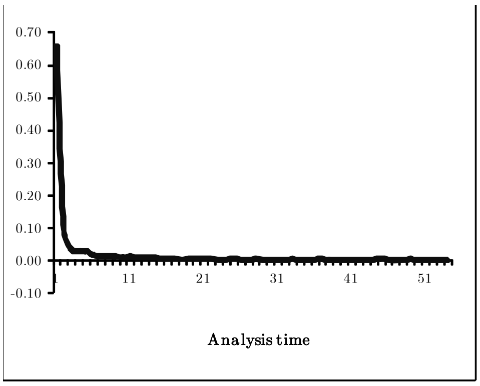
As seen in these figures, the two definitions are substantially different: while in one case around 60% of firms never regain access again (the strict definition of access), in the other case this figure is substantially lower (slightly less than 25%). Despite the differences that are found in the right tails of the survival

Figure 4.5: Time until more access



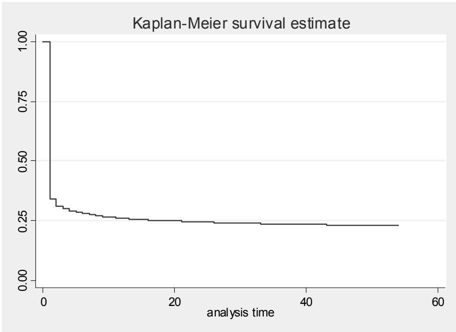
Note: Analysis time defined as quarters since the end of the first default episode. The survivor estimate is defined as the probability of regaining access after default at t: S(t)=Prob(T>=t)=1 - F(t). More access is defined as having a larger amount of outstanding bank loans (including credit lines) than at the end of the default episode and not having any record of default or write-offs.

Figure 4.6: Hazard function for time until access



Note: Analysis time defined as quarters since the end of the first default episode. The hazard function is defined as the probability of regaining access to credit in the time interval [t, t+dt), conditional on not being in default: h(t) = lim Prob(t<=T<t+dt | T>=t)/dt, as dt->0. Access is defined as having a positive amount of outstanding bank loans (including credit lines) without any record of default or write-offs, after having left default.

Figure 4.7: Time until access



Note: Analysis time defined as quarters since the end of the first default episode. The survivor estimate is defined as the probability of regaining access after default at t: S(t)=Prob(T>=t)=1 - F(t). Access is defined as having a positive amount of outstanding bank loans (including credit lines) without any record of default or write-offs, after having left default.

functions, when we compare the two hazard functions we see that their shapes are very similar. In particular, we see that the first 4 to 6 quarters after exiting default are fundamental for determining the ability to regain access to bank credit. When a firm is not able to regain access during this period, the probability of regaining access at any given time becomes very low (almost 0%).

In Table 4.5 we look at different snapshots of the distribution of possible outcomes after default in different moments in time, namely, 1 quarter, 2 quarters, and 1, 2 and 3 years after the first default episode of each firm ends. We consider the same set of outcomes depicted in Table 4.4.

Table 4.5 - Distributions over time of possible outcomes after leaving default

	In credit register										Not in credit register		
	Firms with more access and without		Firms with access (but less than		Firms with access but still with		Firms only with written-off loans (no		Firms in default		Without access or closed		Total
	Number	% of total	Number	% of total	Number	% of total	Number	% of total	Number	% of total	Number	% of total	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Time since first default episode ended													
1 quarter	10,552	12.8	38,022	46.1	7,355	8.9	11,252	13.6	-	-	15,298	18.5	82,479
6 months	9,074	11.4	27,435	34.6	4,994	6.3	10,100	12.7	13,003	16.4	14,792	18.6	79,398
1 year	8,292	11.1	20,314	27.2	3,575	4.8	9,069	12.1	17,914	23.9	15,647	20.9	74,811
2 years	7,172	10.9	14,310	21.7	2,116	3.2	7,953	12.1	16,343	24.8	18,057	27.4	65,951
3 years	6,398	11.0	10,799	18.6	1,777	3.1	6,985	12.0	13,245	22.8	18,805	32.4	58,009

Notes: This table depicts snapshots of the distribution of possible outcomes after default in different moments in time (namely, 1 quarter, 2 quarters and 1, 2 and 3 years after default ends). A default episode is considered resolved if there is no record of loans with late repayments or in litigation in the end of the following quarter. We exclude firms that were in default in 2008Q4, the last quarter in the sample, and consider only the first default episode of each firm during the sample period. After default, firms can either continue to be observed in the credit register (columns 1-10) or they can cease to appear in the CRC (columns 11-12). In the latter case firms can have either ceased to operate or they can still be in operation but without having access to loans from financial institutions. By construction, there are no firms in default in the quarter after the default episode ended. Firms with more access are those with more outstanding bank loans (including credit lines) than at the end of the default episode and without any record of default or write-offs. Firms with less access than before are those which have the same or less loans outstanding that at the end of the default episode.

Regarding the firms that continue to be observed in the CRC database after default, several things happen. First, we see that the percentage of firms with more access and without problem loans is relatively stable over time (column 2). At the same time, the percentage of firms with access to credit, but less than before, decreases substantially as time goes by – it goes from 46% to 19% in 3 years (column 4). This large variation seems to be directly related to recidivism, as after 6 months around 16% of firms are in default again and after 1 year this value is around 24% (column 10). If we add columns (4) and (10) we see that the sum of the two is relatively stable over time. This suggests that a strong indicator of recidivism may be the inability to borrow more than before. Regarding the other possible outcomes, firms with access but still with some written-off loans (columns 5 and 6) and firms only with written-off loans but no access (columns 7 and 8), we observe that over time the number of firms with access and with written off loans decreases substantially while the number of firms without access and with written-off loans does not change much. Finally, with respect to the firms that are not observed in the CRC, we see that this percentage is relatively stable in the first year, but after 2 and 3 years it increases substantially – from around 18% to 30%. This possibly reflects the relatively short life span of micro and small firms, which comprise the bulk of our sample.[66]

4.5.2 Determinants of the duration of exclusion

In order to better understand why some firms are able to regain access to credit relatively fast after exiting default, while other firms are not, we show in Tables 4.6 and 4.7 how the severity of the default episode may help explain

[66] According to Mata and Portugal (1994, 2004), the median life expectancy for Portuguese firms is around 4 to 5 years.

such differences.

Table 4.6 - Characteristics of firms that regain access after their first default episode - broad access definition

	After 1 year								
	Firms with access			Firms without access			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Default severity									
Credit outstanding	28,606	592,326	48,325	24,716	66,795	7,292	525,532	8.9	0.00
Credit overdue	28,606	29,743	1,900	24,716	23,310	2,840	6,433	3.2	0.00
Credit overdue ratio	28,606	20.9	5	24,716	83.5	100.0	-62.6	-230.0	0.00
Write-offs	28,606	1,774	0	24,716	19,336	0	-17,562	-17.1	0.00
Loss estimates (%)	28,606	0.8	0	24,716	14.2	0	-13.5	-69.2	0.00
Duration of default	28,606	2.4	1	24,716	7.5	5	-5.2	-94.9	0.00
Relationships									
No. of bank relationships	28,606	2.8	2	24,716	1.3	1	1.5	121.36	0.00
No. of bank relat. in default	28,606	1.1	1	24,716	1.2	1	-0.1	-30.71	0.00
No. of bank relat. in default %	28,606	54.2	50	24,716	95.0	100	-40.8	-200.0	0.00
Default with main bank	28,606	0.5	1	24,716	0.9	1	-0.4	-100.0	0.00

	After 3 years								
	Firms with access			Firms without access			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Default severity									
Credit outstanding	17,197	643,922	57,860	25,790	81,531	10,050	562,391	8.1	0.00
Credit overdue	17,197	33,087	2,020	25,790	22,179	2,644	10,908	4.1	0.00
Credit overdue ratio	17,197	21.1	5	25,790	69.6	100.0	-48.5	-140.0	0.00
Write-offs	17,197	2,183	0	25,790	13,736	0	-11,553	-12.6	0.00
Loss estimates (%)	17,197	1.0	0	25,790	10.5	0	-9.5	-55.0	0.00
Duration of default	17,197	2.4	1	25,790	5.7	3	-3.3	-72.8	0.00
Relationships									
No. of bank relationships	17,197	3.0	2	25,790	1.5	1	1.5	91.1	0.00
No. of bank relat. in default	17,197	1.1	1	25,790	1.2	1	-0.1	-20.88	0.00
No. of bank relat. in default %	17,197	51.2	50	25,790	87.8	100	-36.6	-140.0	0.00
Default with main bank	17,197	0.5	1	25,790	0.8	1	-0.3	-74.0	0.00

Notes: Firms with access are those with outstanding bank loans (including credit lines) and without any record of default or write-offs after 1 year (columns 1 - 3) or 3 years (columns 9-11). Firms without access are those that are not in the credit register after leaving default, as well as those which continue to be present in the credit register, but only with written-off loans. The results for 1 year after default exclude firms that defaulted for the first time in 2008 and the results for 3 years after default exclude firms that defaulted for the first time in 2006, 2007 or 2008. All variables are defined as in previous tables and refer to the last period of default. Mean difference tests are computed assuming unequal variances in the two groups considered.

Table 4.7 - Characteristics of firms that regain access after their first default episode - strict access definition

	After 1 year								
	Firms with more access than before			Firms without access or with less access than before			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Default severity									
Credit outstanding	8,292	934,087	56,871	45,030	240,940	17,971	693,147	4.5	0.00
Credit overdue	8,292	29,349	1,490	45,030	26,284	2,490	3,064	1.1	0.28
Credit overdue ratio	8,292	21.4	4	45,030	55.2	63.4	-33.8	-79.8	0.00
Write-offs	8,292	3,554	0	45,030	11,085	0	-7,531	-6.1	0.00
Loss estimates (%)	8,292	1.1	0	45,030	8.1	0	-7.0	-49.7	0.00
Duration of default	8,292	2.3	1	45,030	5.2	2	-2.9	-65.8	0.00
Relationships									
No. of bank relationships	8,292	3.0	2	45,030	1.9	1	1.1	44.4	0.00
No. of bank relat. in default	8,292	1.1	1	45,030	1.1	1	-0.1	-21.3	0.00
No. of bank relat. in default %	8,292	51.1	50	45,030	77.1	100	-26.0	-71.6	0.00
Default with main bank	8,292	0.5	0	45,030	0.7	1	-0.3	-44.3	0.00

	After 3 years								
	Firms with more access than before			Firms without access or with less access than before			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Default severity									
Credit outstanding	6,398	696,117	44,875	36,589	238,390	17,550	457,727	3.5	0.00
Credit overdue	6,398	23,552	1,329	36,589	27,066	2,640	-3,513	-1.5	0.12
Credit overdue ratio	6,398	23.2	5	36,589	54.9	58.8	-31.7	-64.5	0.00
Write-offs	6,398	2,784	0	36,589	10,221	0	-7,437	-7.1	0.00
Loss estimates (%)	6,398	1.0	0	36,589	7.6	0	-6.6	-43.3	0.00
Duration of default	6,398	2.3	1	36,589	4.7	2	-2.5	-54.9	0.00
Relationships									
No. of bank relationships	6,398	3.0	2	36,589	1.9	1	1.1	37.0	0.00
No. of bank relat. in default	6,398	1.1	1	36,589	1.1	1	-0.1	-20.0	0.00
No. of bank relat. in default %	6,398	52.3	50	36,589	76.8	100	-24.5	-58.7	0.00
Default with main bank	6,398	0.5	0	36,589	0.7	1	-0.3	-37.6	0.00

Notes: Firms with more access are those with more outstanding bank loans (including credit lines) than at the end of the default episode and without any record of default or write-offs after 1 year (columns 1 - 3) or 3 years (columns 9-11). Firms without access or with less access than before are those that are not in the credit register after leaving default, those that continue to be present in the credit register, but only with written-off loans, as well as those that have the same or less loans outstanding that at the end of the default episode. The results for 1 year after default exclude firms that defaulted for the first time in 2008 and the results for 3 years after default exclude firms that defaulted for the first time in 2006, 2007 or 2008. All variables are defined as in previous tables and refer to the last period of default. Mean difference tests are computed assuming unequal variances in the two groups considered.

In these two tables we compare various default severity measures (credit outstanding, credit overdue, existence of write-offs, duration of default) for firms that were able to regain access after 1 and 3 years and for firms that were not. In Table 4.6 we consider the broader definition of access, whereas in Table 4.7 we provide similar results for the stricter definition. In all cases we systematically find that the probability of regaining access is lower when the default events are longer and more severe. This is not surprising and to some extent it should be expected. This result reflects not only the fact that banks will impose harsher punishments on firms that generate more losses, but it also reflects the fact that firms that generate more losses are also those with greater financial problems and are therefore less creditworthy.

We also observe that larger firms regain access to credit more easily than smaller firms. The same is true for firms that hold more bank relationships, though this may be correlated with firm size. Our interpretation is that large firms are usually perceived as less risky and more stable. Therefore, banks are willing to extend credit faster to large firms than to small firms. Another result we obtain is that firms that default with their main bank lender also face more difficulties in regaining access to bank loans. This result, together with the effect of holding more bank relationships, reflects the costs firms may have when their pool of lenders is not sufficiently diversified. Thus, when the relationship between a borrower and a lender is interrupted due to financial distress, firms will face more difficulties in regaining access to credit if they borrow from one or a few banks or if they default with their main lender. This increased difficulty should reflect the destruction of value that had previously been created through that relationship, as smaller and opaque firms transmit valuable information to their lenders over time, which cannot be easily transferred to a new bank relationship.

In order to test whether the previous results hold in a multivariate setting and at the same time to be able to tell which factors matter more for the speed of re-access, we estimate a Cox proportional hazard model for the time to access, such that:

$$h(t, X_i) = \psi(X_i, \beta)h_0$$

where $\psi(.)$ is a non-negative function of X_i and β, the vectors of covariates and parameters, and h_0 is the baseline hazard. In this model, the baseline hazard is common to all firms and individual hazard functions differ from each other proportionally, with $\psi(.)$ representing the factor of proportionality. One advantage of this method is that it is a semi-parametric approach, thereby allowing us to estimate β without specifying the form of the baseline hazard. Under this setup, the covariates do not affect the shape of the overall hazard function, conditioning only the relative failure risk of each firm. The failure risk is defined as the time until a firm regains access to credit (using our two different definitions of access) after it has resolved its first default episode.

The estimation results, which are presented in the form of hazard ratios, are shown in Table 4.8.[67] Columns (1) to (4) refer to the broad access definition, whereas columns (5) to (8) consider the strict definition. The differences between the columns reflect the type of time controls used.

[67] In these regressions, an estimated coefficient below (above) 1, should be interpreted as contributing to a longer (shorter) time until the firm regains access to credit.

Table 4.8 - Cox regressions: determinants of time until access

	All firms							
	Failure event: access (broad definition)				Failure event: access (strict definition)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln Credit outstanding (ln(euros))	1.016	1.015	1.015	1.015	1.010	1.008	1.007	1.008
	0.00	*0.00*	*0.00*	*0.00*	*0.04*	*0.08*	*0.12*	*0.08*
Credit overdue ratio (%)	0.993	0.993	0.993	0.993	0.998	0.997	0.997	0.997
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Loss rate (%)	0.974	0.974	0.974	0.974	0.980	0.980	0.980	0.980
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Duration of default (quarters)	0.937	0.939	0.940	0.939	0.921	0.927	0.928	0.927
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
No. of bank relationships	0.957	0.956	0.957	0.956	1.010	1.008	1.007	1.008
	0.00	*0.00*	*0.00*	*0.00*	*0.07*	*0.15*	*0.16*	*0.15*
No. of bank relat. in default % of total	0.996	0.996	0.996	0.996	0.994	0.994	0.994	0.994
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Default with main bank (binary)	1.058	1.063	1.063	1.063	0.877	0.896	0.898	0.896
	0.00	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Recession (binary)	-	-	-	1.092	-	-	-	1.103
	-	-	-	*0.00*	-	-	-	*0.06*
D_1996	-	1.145	-	1.145	-	1.421	-	1.421
	-	*0.00*	-	*0.00*	-	*0.00*	-	*0.00*
D_1997	-	1.170	-	1.170	-	1.335	-	1.335
	-	*0.00*	-	*0.00*	-	*0.00*	-	*0.00*
D_1998	-	1.159	-	1.159	-	1.424	-	1.425
	-	*0.00*	-	*0.00*	-	*0.00*	-	*0.00*
D_1999	-	0.977	-	0.977	-	1.515	-	1.515
	-	*0.05*	-	*0.05*	-	*0.00*	-	*0.00*
D_2000	-	1.010	-	1.010	-	1.326	-	1.326
	-	*0.34*	-	*0.34*	-	*0.00*	-	*0.00*
D_2001	-	1.040	-	1.040	-	1.485	-	1.485
	-	*0.00*	-	*0.00*	-	*0.00*	-	*0.00*
D_2002	-	0.996	-	0.996	-	1.226	-	1.226
	-	*0.63*	-	*0.63*	-	*0.00*	-	*0.00*
D_2003	-	1.039	-	0.952	-	0.967	-	0.877
	-	*0.00*	-	*0.00*	-	*0.26*	-	*0.03*
D_2004	-	0.932	-	0.912	-	0.852	-	0.831
	-	*0.00*	-	*0.00*	-	*0.00*	-	*0.00*
D_2005	-	0.990	-	0.990	-	0.856	-	0.856
	-	*0.27*	-	*0.27*	-	*0.00*	-	*0.00*
D_2006	-	0.951	-	0.951	-	0.916	-	0.916
	-	*0.00*	-	*0.00*	-	*0.00*	-	*0.00*
D_2007	-	0.982	-	0.982	-	1.085	-	1.085
	-	*0.02*	-	*0.02*	-	*0.00*	-	*0.00*
Quarter dummies	N	N	Y	N	N	N	Y	N
Number of subjects	73,980	73,980	73,980	73,980	73,980	73,980	73,980	73,980
Number of failures	54,282	54,282	54,282	54,282	21,055	21,055	21,055	21,055
Time at risk	384,240	384,240	384,240	384,240	893,125	893,125	893,125	893,125
Log-likelihood	-589,282	-589,180	-589,097	-589,177	-226,434	-226,022	-225,864	-226,020

Notes: p-values in italics. All models estimated using a Cox regression that evaluates the time until access using robust variance estimates. An estimated coefficient lower than 1 should be interpreted as contributing a longer time until access. In columns (1) - (4), the dependent variable is the time until access using the broad definition (see Table 6). In columns (5) - (8) it is considered the strict definition of access (see Table 7). All explanatory variables are defined as in previous tables (except recession, which is a dummy variable that takes the value one in recession years) and refer to the last period of default.

The results are broadly consistent with those of Tables 4.6 and 4.7. Taking the total amount of credit outstanding as a proxy for firm size, we observe that larger firms regain access faster (columns (1)-(4)). However, this result is not strongly statistically significant when we consider the time it takes a firm to regain access to a new bank loan after default (columns (5)-(8)). The intensity of the default episode is a key determinant in the process of regaining access: firms that have higher credit overdue ratios and higher loss rates take more time to regain access to credit, especially when the broad definition of access is considered. The impact of default duration goes in the same direction, but now the effect is stronger for the stricter access definition, i.e., a longer default inhibits the ability of firms to gain access to new bank loans.

The choice of the number of bank relationships also seems to influence how easily firms regain access to bank credit after default, though only in the broader definition case.[68] Firms that borrow from more banks take more time to regain access to bank loans. This result is not entirely in line with the insights we gained from Table 4.6, where we observed that firms with more bank relationships were more likely to regain access. However, this previous result could be somewhat influenced by the strong correlation between firm size and the number of bank relationships. This fact may explain why this

[68] The results for the stricter definition are not statistically significant at a 5% level.

result does not hold in a multivariate setting. Indeed, when controlling for the total amount of credit outstanding of each firm, we observe that firms with many bank relationships may actually have more difficulties in regaining access to bank loans. Hence, engaging in single bank relationships may provide some benefits for firms in financial distress.[69] We also find that firms that default on a larger percentage of existing bank relationships take more time to regain access to credit, which may also be regarded as evidence that more severe default episodes lead to a more prolonged exclusion from credit markets.

Finally, with respect to firms that default with their main lender, the results are rather mixed: these firms seem to have more difficulties in gaining access to new loans, but the opposite happens when the broad definition of access is considered. This result is likely driven by the way we define access in the latter case: a firm regains access when it records a positive amount of credit outstanding without having any problem loans. Thus, if a firm defaults for a given period of time and at some point it is able to repay the overdue debt, we consider that the firm has regained access. As we observe that most firms actually default with their main lender, the time it takes to regain access may

[69]For instance, Carmignani and Omiccioli (2007) argue that the overall effect of more concentrated banking relationships is a lower probability of liquidation, but a higher probability of financial distress. In turn, Elsas and Krahnen (1998) show that when there are strong bank-customer relationships, banks provide liquidity insurance to firms in financial distress.

be mechanically driven by this feature of the data.

As mentioned above, the different columns in Table 4.8 consider essentially the same explanatory variables, with the exception of time controls. Time effects seem to play a relevant role: firms that emerged from default in the earlier years of our sample took less time to regain access to credit than firms that defaulted in more recent years. In order to better explore these effects, in columns (4) and (8) we include a binary variable for recession years. We find that firms that exit default during recessions are able to regain access to bank loans sooner, controlling for all other default and loan characteristics. This is an interesting result, as it suggests that when a firm is able to resolve an adverse situation during adverse times, banks perceive this as being a signal of the quality and strength of the firm.[70] In particular, banks possibly consider that these firms are of higher quality (in terms of creditworthiness) and therefore grant credit faster than if the default resolution had happened in non-recession years.[71] Moreover, these firms are more likely to have defaulted

[70]For robustness purposes, we also consider the effect of entering default during a recession on the time it takes until firms regain access to credit, but the results are not statistically significant. In addition, we also consider simultaneously the effect of entering and/or leaving default during a recession, plus an interaction between these two possibilities (i.e., a binary variable that takes the value 1 when the firm enters and leaves default during a recession). If this is the case, firms are able to regain access significantly faster. In contrast, firms that entered default during a recession should take more time to regain access. The effect of leaving default during a recession is not significant in this specification.

[71]Acharya et al. (2007) study the impact of industry-wide distress on the recoveries of defaulted firms in the US and find that defaulting firms that belong to industries in distress are more likely to spend more time in bankruptcy. However, these firms are also more likely

due to an exogenous systematic shock than due to idiosyncratic fragilities, which supports the creditworthiness assessment made by banks.[72]

4.5.3 Access and bank choice

Thus far, we observed that many firms are able to borrow again from banks after resolving a default, but only a small percentage have access to new bank loans. A key issue in this analysis is then to look at which banks are granting these new bank loans. Are firms borrowing from the banks with whom they had ongoing bank relationships before the default or are they borrowing from new banks? In Table 4.9 we provide some preliminary results on this question.

to be restructured than to be acquired or liquidated.

[72] For robustness purposes, we also estimate probit regressions where the dependent variable is a dummy variable (d_i), indicating whether the firm regains access to credit in the 3 years after leaving default ($d_i = 1$) or not ($d_i = 0$), for both access definitions. The results are qualitatively consistent with those obtained with duration analysis, with the exception of those relating to the recession variable, which has a negative coefficient in the probit regressions. These results are available upon request.

Table 4.9 - Regaining access through new banks

	After 1 quarter			After 1 year			After 3 years		
	Firms with more access	Firms with more access and with a new bank		Firms with more access	Firms with more access and with a new bank		Firms with more access	Firms with more access and with a new bank	
			%			%			%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1995	330	136	41.2	-	-	-	-	-	-
1996	641	226	35.3	356	210	59.0	-	-	-
1997	604	200	33.1	467	282	60.4	-	-	-
1998	538	214	39.8	529	291	55.0	349	265	75.9
1999	761	227	29.8	534	318	59.6	505	371	73.5
2000	545	223	40.9	469	292	62.3	564	424	75.2
2001	1,189	559	47.0	541	385	71.2	569	481	84.5
2002	1,091	412	37.8	1,239	811	65.5	411	342	83.2
2003	957	262	27.4	766	432	56.4	456	388	85.1
2004	752	188	25.0	670	389	58.1	997	804	80.6
2005	577	171	29.6	630	375	59.5	719	562	78.2
2006	662	160	24.2	547	322	58.9	657	509	77.5
2007	985	266	27.0	652	366	56.1	629	506	80.4
2008	920	177	19.2	892	464	52.0	542	427	78.8
Total	10,552	3,421	32.4	8,292	4,937	59.5	6,398	5,079	79.4

Notes: Firms with more access are those with more outstanding bank loans (including credit lines) than at the end of the default episode and without any record of default or write-offs. Firms with more access and with a new bank defined as those borrowing from a bank which was not a lender when the default episode ended. Only firms with less than 9 bank relationships are considered.

We previously saw that, in the quarter immediately after the default episode is cleared, 13% of firms have access to a new bank loan (Table 4.4). From this group of firms, almost one third of the firms obtain that new loan from a bank with which they had no relationship when the default was resolved (Table 4.9). This percentage is higher in the first years of the sample period. When we examine this situation one and three years after default, we observe that the percentage of firms that obtained a loan from a new lender increases markedly:

60% after one year and 80% after 3 years.

These results must be analyzed bearing in mind that the CRC is designed to be an information sharing mechanism between banks. When a firm defaults on a bank loan, the other banks currently lending to the firm can observe that. Prospective lenders can also ask to have access to that information, with the firms' consent, which is usually the common procedure. Notwithstanding this, banks seem to be generally willing to give firms a second chance. However, as mentioned before, it should be noted that the CRC only includes the current status of bank loans. Thus, participating banks cannot observe the history of past defaults for new borrowers.

In Table 4.10 we compare firms that regain access through an existing bank relationship to firms that regain access through a new bank relationship. We consider only the strict definition of access, as this analysis is relevant only for obtaining new bank loans. We observe that firms that are able to borrow from a new bank are, on average, smaller, and have fewer bank relationships. This result may be somewhat unexpected, but possibly reflects the fact that banks may be reluctant to lend to firms that defaulted and, simultaneously, have many bank relationships (or, alternatively, firms that already have many bank relationships may find it too costly to engage in additional relationships). Firms that obtain a loan from a new bank are also slightly more likely to have defaulted to their main lender, possibly suggesting that if a firm defaults with its most important provider of funds, it may be more likely that it is forced to look for a new lender, as the former main bank may not be willing to extend new loans to the firm. Default duration and severity do not seem to be relevant in explaining why some firms are not able to obtain loans from a new lender.

Table 4.10 - Characteristics of firms that regain access with a new bank after their first default episode (strict definition)

	After 1 year								
	Firms with more access than before and a new bank			Firms with more access than before but not with a new bank			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Default severity									
Credit outstanding	4,937	451,545	48,400	3,355	1,644,164	73,480	-1,192,619	-3.3	0.00
Credit overdue	4,937	22,214	1,221	3,355	39,848	2,150	-17,635	-2.9	0.00
Credit overdue ratio	4,937	20.9	4	3,355	22.1	4.0	-1.2	-1.6	0.10
Write-offs	4,937	3,151	0	3,355	4,149	0	-998	-0.5	0.65
Loss estimates (%)	4,937	1.0	0	3,355	1.2	0	-0.1	-0.8	0.44
Duration of default	4,937	2.3	1	3,355	2.3	1	-0.1	-1.0	0.32
Relationships									
No. of bank relationships	4,937	2.9	3	3,355	3.3	2	-0.4	-7.1	0.00
No. of bank relat. in default	4,937	1.1	1	3,355	1.1	1	0.0	-1.5	0.14
No. of bank relat. in default %	4,937	51.8	50	3,355	50.1	50	1.7	2.5	0.01
Default with main bank	4,937	0.5	0	3,355	0.5	0	0.0	1.8	0.07

	After 3 years								
	Firms with more access than before and a new bank			Firms with more access than before but not with a new bank			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Default severity									
Credit outstanding	5,079	345,756	42,100	1,319	2,045,234	61,860	-1,699,478	-2.8	0.01
Credit overdue	5,079	21,043	1,180	1,319	33,217	2,245	-12,174	-2.1	0.03
Credit overdue ratio	5,079	23.2	5	1,319	23.1	4.2	0.1	0.1	0.90
Write-offs	5,079	2,351	0	1,319	4,450	0	-2,099	-0.8	0.44
Loss estimates (%)	5,079	0.9	0	1,319	1.5	0	-0.6	-2.1	0.04
Duration of default	5,079	2.3	1	1,319	2.2	1	0.1	0.8	0.40
Relationships									
No. of bank relationships	5,079	2.8	2	1,319	3.6	2	-0.7	-7.6	0.00
No. of bank relat. in default	5,079	1.1	1	1,319	1.1	1	0.0	-0.6	0.53
No. of bank relat. in default %	5,079	53.1	50	1,319	49.0	50	4.1	4.3	0.00
Default with main bank	5,079	0.5	0	1,319	0.4	0	0.1	3.3	0.00

Notes: Firms with more access and a new bank are those with more outstanding bank loans from a new bank (including credit lines) than at the end of the default episode and without any record of default or write-offs after 1 year (columns 1 - 3) or 3 years (columns 9-11). Firms with more access than before but not with a new bank have the same characteristics, with the exception of borrowing from a new bank. The results for 1 year after default exclude firms that defaulted for the first time in 2008 and the results for 3 years after default exclude firms that defaulted for the first time in 2006, 2007 or 2008. Only firms with less than 9 bank relationships are considered. All variables are defined as in previous tables and refer to the last period of default. Mean difference tests are computed assuming unequal variances in the two groups considered.

In order to see if the previous results hold under a multivariate framework, and at the same time to get estimates of the relative importance of each of the factors, we estimate a probit model for the event of accessing credit through an existing bank relationship or through a new one. The dependent variable in this model is a binary variable (d_i) indicating whether the firm had access to a new bank loan with the same bank ($d_i = 0$) or with a new bank ($d_i = 1$). We consider the same explanatory variables presented in Table 4.8 and add a variable indicating the duration of exclusion (i.e., the time elapsed since the default is cleared until the firm obtains a new loan under our strict access definition). Table 4.11 presents the results of these regressions.

Table 4.11 - Probit regressions: determinants of the likelihood of obtaining a new loan from a new bank

	Dependent variable: access with a new bank (strict definition)			
	(1)	(2)	(3)	(4)
Ln Credit outstanding (ln(euros))	-0.082	-0.079	-0.082	-0.079
	0.00	*0.00*	*0.00*	*0.00*
Credit overdue ratio (%)	-0.003	-0.003	-0.003	-0.003
	0.00	*0.00*	*0.00*	*0.00*
Loss rate (%)	0.003	0.003	0.002	0.003
	0.01	*0.01*	*0.04*	*0.01*
Duration of default (quarters)	-0.004	-0.004	-0.003	-0.004
	0.19	*0.22*	*0.37*	*0.22*
No. of bank relationships	-0.013	-0.016	-0.014	-0.016
	0.06	*0.03*	*0.04*	*0.03*
No. of bank relat. in default % of total	0.000	0.000	0.000	0.000
	0.54	*0.86*	*0.98*	*0.86*
Default with main bank (binary)	0.023	0.029	0.036	0.030
	0.32	*0.21*	*0.12*	*0.19*
Duration of exclusion (quarters)	-0.018	-0.016	-0.016	-0.016
	0.00	*0.00*	*0.00*	*0.00*
Constant	0.871	0.583	0.545	0.583
	0.00	*0.00*	*0.00*	*0.00*
Recession (binary)	-	-	-	0.145
	-	-	-	*0.04*
Year dummies	N	Y	N	Y
Quarter dummies	N	N	Y	N
Number of observations	21,055	21,055	21,055	21,055
Pseudo R2	0.02	0.03	0.04	0.03
Wald test	315.7	609.1	867.2	613.8
Log pseudolikelihood	-14,110	-13,970	-13,836	-13,968

Notes: p-values in italics. All models estimated using a probit regression using robust variance estimates. The dependent variable is a binary variable that takes the value 1 if the firm is able to obtain a new loan from a new bank within the 3 years after its first default episode is resolved; and takes the value 0 if the firm obtains a new loan in the same situation, but not from a new bank (see Table 10). Only firms with less than 9 bank relationships are considered. All explanatory variables are defined as in previous tables (except for the duration of exclusion, which measures the number of quarters since the default is resolved until the firm obtains a new loan under our strict access definition) and refer to the last period of default.

These results indicate that, in agreement with the results of Table 4.10, the larger the firm is, the less likely it will obtain a loan from a new bank. The results regarding the number of bank relationships and default with the main bank are also consistent with those of Table 4.10. Furthermore, we also find that firms with higher credit overdue ratios are less likely to establish a new bank relationship after default, even though we find the opposite result for the loss rate. Thus, the results on default severity are not clear cut. The duration of exclusion has a negative impact on the likelihood of obtaining a new loan with a new bank: the longer a firm takes to obtain a new bank loan, the less likely it is that this new loan will be granted by a new bank. Finally, the recession variable also plays an important role, in line with the results of the previous subsection. When a firm emerges from default during a recessionary episode, it is much easier to obtain a loan from a new bank than otherwise.[73]

4.5.4 Recidivism

Thus far we have shown that many firms are able to regain access to credit markets after default. The probability of regaining access is especially high in

[73] For robustness purposes, we also estimate the regressions presented in Table 11 using a logit model. The results are remarkably consistent, with the exception of the explanatory power of the number of bank relationships: while in the probit regressions this variable is marginally statistically significant to explain the likelihood of obtaining a new loan from a new bank (with a negative impact), in the logit regressions this variable is not statistically significant.

the quarters immediately after the default is resolved. If a firm is not able to regain access during the first few quarters after default, it is very unlikely that it ever will. Many banks are willing to give firms a second chance and some banks may offer a loan to a new customer even if they had a default episode in their recent past.

However, an interesting, and somewhat surprising, result we obtain relates to the high levels of recidivism. Previously, in Table 4.5, we showed that after 6 months around 16% of firms were in default again, and after 1 year this number increases to 24%. In fact, as shown in Table 4.4, almost half of the firms default again during the 3 years after their first default episode is resolved. In order to better understand why some firms default again while others do not, we conduct an analysis similar to those in Tables 4.6 and 4.7, but for the event of a firm defaulting again. The results are presented in Table 4.12 for the broad access definition.

Table 4.12 - Characteristics of firms that regain access but default again

	After 1 year								
	Firms again in default			Firms with access and without default			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Default severity									
Credit outstanding	17,914	318,697	39,469	28,606	592,326	48,325	-273,630	-4.5	0.00
Credit overdue	17,914	27,630	3,250	28,606	29,743	1,900	-2,112	-1.0	0.34
Credit overdue ratio	17,914	36.0	12	28,606	20.9	5	15.1	42.0	0.00
Write-offs	17,914	12,114	0	28,606	1,774	0	10,341	5.8	0.00
Loss estimates (%)	17,914	5.4	0	28,606	0.8	0	4.6	31.8	0.00
Duration of default	17,914	4.1	2	28,606	2.4	1	1.7	38.5	0.00
Relationships									
No. of bank relationships	17,914	2.5	2	28,606	2.8	2	-0.2	-13.1	0.00
No. of bank relat. in default	17,914	1.2	1	28,606	1.1	1	0.1	32.8	0.00
No. of bank relat. in default %	17,914	65.2	50	28,606	54.2	50	11.0	36.9	0.00
Default with main bank	17,914	0.6	1	28,606	0.5	1	0.1	22.7	0.00

	After 3 years								
	Firms again in default			Firms with access and without default			Mean difference		
	Obs.	Mean	Median	Obs.	Mean	Median	diff	t-test	p-value
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Default severity									
Credit outstanding	13,245	397,972	57,080	17,197	643,922	57,860	-245,950	-3.2	0.00
Credit overdue	13,245	33,277	4,065	17,197	33,087	2,020	190	0.1	0.95
Credit overdue ratio	13,245	32.4	9	17,197	21.1	5	11.3	26.6	0.00
Write-offs	13,245	14,574	0	17,197	2,183	0	12,392	4.9	0.00
Loss estimates (%)	13,245	4.9	0	17,197	1.0	0	3.9	23.7	0.00
Duration of default	13,245	3.6	2	17,197	2.4	1	1.2	26.1	0.00
Relationships									
No. of bank relationships	13,245	2.9	2	17,197	3.0	2	-0.1	-4.5	0.00
No. of bank relat. in default	13,245	1.2	1	17,197	1.1	1	0.1	26.3	0.00
No. of bank relat. in default %	13,245	59.2	50	17,197	51.2	50	8.1	22.4	0.00
Default with main bank	13,245	0.6	1	17,197	0.5	1	0.1	12.9	0.00

Notes: Firms again in default are those that record a new default episode after 1 year (columns 1-3) or 3 years (columns 9-11). Firms with access are those with outstanding bank loans (including credit lines) and without any record of default or write-offs after 1 year (columns 4 - 6) or 3 years (columns 12-14). The results for 1 year after default exclude firms that resolved their first default episode in 2008 and the results for 3 years after default exclude firms that resolved their first default episode in 2006, 2007 or 2008. All variables are defined as in previous tables and refer to the last period of default. Mean difference tests are computed assuming unequal variances in the two groups considered.

From Table 4.12 we see that firms that default again are, on average, smaller and their initial default episode was longer and more severe.

In Table 4.13, we present the results of Cox regressions, having as a dependent variable the time it takes for a firm to default again after having resolved the first default episode.

Table 4.13 - Cox regressions: determinants of time until new default

	Failure event: new default			
	(1)	(2)	(3)	(4)
Ln Credit outstanding (ln(euros))	1.033	1.032	1.032	1.032
	0.00	*0.00*	*0.00*	*0.00*
Credit overdue ratio (%)	0.995	0.994	0.994	0.994
	0.00	*0.00*	*0.00*	*0.00*
Loss rate (%)	0.997	0.997	0.997	0.997
	0.00	*0.00*	*0.00*	*0.00*
Duration of default (quarters)	0.987	0.989	0.990	0.989
	0.00	*0.00*	*0.00*	*0.00*
No. of bank relationships	1.031	1.029	1.029	1.029
	0.00	*0.00*	*0.00*	*0.00*
No. of bank relat. in default % of total	1.002	1.002	1.002	1.002
	0.00	*0.00*	*0.00*	*0.00*
Default with main bank (binary)	1.165	1.176	1.178	1.176
	0.00	*0.00*	*0.00*	*0.00*
Recession (binary)	-	-	-	0.833
	-	-	-	*0.00*
D_1996	-	1.390	-	1.389
	-	*0.00*	-	*0.00*
D_1997	-	1.502	-	1.502
	-	*0.00*	-	*0.00*
D_1998	-	0.967	-	0.967
	-	*0.25*	-	*0.25*
D_1999	-	1.221	-	1.221
	-	*0.00*	-	*0.00*
D_2000	-	0.990	-	0.990
	-	*0.70*	-	*0.70*
D_2001	-	1.069	-	1.068
	-	*0.00*	-	*0.00*
D_2002	-	1.110	-	1.110
	-	*0.00*	-	*0.00*
D_2003	-	1.018	-	1.221
	-	*0.39*	-	*0.00*
D_2004	-	0.853	-	0.890
	-	*0.00*	-	*0.00*
D_2005	-	0.873	-	0.873
	-	*0.00*	-	*0.00*
D_2006	-	0.910	-	0.910
	-	*0.00*	-	*0.00*
D_2007	-	1.144	-	1.144
	-	*0.00*	-	*0.00*
D_2008	-	-	-	-
	-	-	-	-
Quarter dummies	N	N	Y	N
Number of subjects	73,980	73,980	73,980	73,980
Number of failures	39,756	39,756	39,756	39,756
Time at risk	681,425	681,425	681,425	681,425
Log-likelihood	-420,012	-419,623	-419,009	-419,613

Notes: p-values in italics. All models estimated using a Cox regression that evaluates the time until a new default, using robust variance estimates. An estimated coefficient lower than 1 should be interpreted as contributing a longer time until default. The dependent variable is the time until a new default occurs after the first default episode is resolved. All explanatory variables are defined as in previous tables and refer to the last period of default.

We find that firms are more likely to default again if they are larger, have more bank relationships, and if they have defaulted with their main lender. Quite surprisingly, firms with more severe and longer defaults take more time to default again. However, this last result deserves a more careful analysis. In fact, this repeated default is conditional on regaining access to credit which, as we found previously, is less likely for firms with long and severe episodes of financial distress.[74]

As before, we explore the time effects, observing that these are indeed significant. In fact, when we control for whether firms emerged from default during a recession, we observe that if this is the case then the firm is less likely to default again. Thus, if a firm is able to overcome the severe financial distress that led to a bank loan default during a recession, its future default probability declines significantly.

[74] For robustness purposes, we run the same regressions, but conditional on firms regaining access to new bank loans, i.e., the strict access definition. The results are qualitatively similar, with the exception of default duration: firms with longer distress episodes default faster, conditional on having regained access to a new bank loan after default. The variable number of bank relationships also becomes statistically insignificant. These results are available upon request.

4.6 Conclusions

In this chapter we investigate several questions: What happens to firms after they default on their bank loan obligations?; What happens to firms while they are in default?; How many firms are able to overcome financial distress and regain access to bank credit?; Which default characteristics influence these outcomes? To address these questions we use a unique dataset from Portugal, the Central Credit Register, which gathers information on all loans above 50 euros that are granted by any financial institution operating in Portugal.

We first analyze what happens while firms are still "in default" and, in the second part of the chapter, we examine what happens after firms are no longer classified as "in default".

With respect to the "in default" period, our main findings are:

i) Defaults became more frequent during the sample period, but also became less severe and involved smaller amounts;

ii) The median duration of default is 5 quarters, and this value had some variation over time;

iii) Default episodes can either be very short-lived or very long. If a default episode is not resolved within 1 year, it can take several years to be cleared;

iv) The duration of default is positively correlated with its severity. Moreover, firms that stay longer in default are typically firms that entered default in worse conditions than the ones that exit faster; and

v) Of all the default events that we analyze, only one third of these lead to write-offs. For those loans that lead to a write-off, the average loss incurred by banks is around 34%, while the average loss when all loans are considered (i.e., with and without write-offs) is slightly above 10%.

Regarding what happens after the default episode is cleared, our main results are:

i) In the first quarter after leaving default, almost two thirds of firms have access to credit again, but only one quarter is able to get a new bank loan;

ii) Exclusion from credit markets is either very short or very long. Firms that are not able to regain access in the first year after exiting default are very unlikely to ever regain access;

iii) The severity of the default impacts the duration of exclusion: the more severe the default was, the longer the firm is unable to borrow. This is true for the amount defaulted on, the amount that was written-off, and the duration of default;

iv) Firms regain access mainly with the banks with whom they had previously ongoing relationships. However, as time goes by, firms are more likely to regain access through new bank relationships;

v) There is a very high rate of recidivism: one year after exiting default, almost 25% of firms are in default again. We find that recidivism is related to the severity of default; and

vi) Firms that leave default during recession periods regain access to credit faster and are less likely to default again.

These results provide valuable empirical evidence on corporate post-default dynamics, an issue that, in our opinion, has not been sufficiently explored in the literature. However, many questions remain unanswered, some of which are raised by the results discussed above. Two of these questions that we plan to tackle in future research are whether banks charge higher interest rates to firms after a default and also what factors can explain the high rates of recidivism?

CHAPTER 5

5 Counterfactual Analysis of Bank Mergers

5.1 Introduction

We analyze the effects bank mergers exert on market structure and credit conditions[75]. The conventional approach employed in the banking literature relies on the comparison of market characteristics before and after the mergers, overlooking endogenous changes in market structure in the post-merger equilibrium in the banking system. In this chapter, we present a methodology that allows overcoming this gap in the evaluation of merger impact in banking. By deriving a structural model of the credit market, we are able to perform a counterfactual analysis of mergers, combining the pre-merger equilibrium setting with characteristics of the post-merger environment, while accounting for endogenously propagated changes in market structure. Using this procedure we are able to estimate loan flows and interest rates that would be observed if the pre-merger equilibrium was not altered, i.e., if mergers had not occurred. We obtain estimates of the impact of mergers accounting for the

[75] This chapter is based on joint work with Pedro Pita Barros, Moshe Kim and Nuno Martins, published as Barros, P.P., D. Bonfim, M. Kim and N. Martins (2013), Counterfactual Analysis of Bank Mergers, Empirical Economics, forthcoming.

effects associated with endogenous changes in conduct and market structure after mergers have taken place. Moreover, we disentangle the effect of changes in the macroeconomic and financial environment from endogenous changes in market structure resulting from the mergers. These effects are usually ignored in the assessment of merger impact and can lead to a significant bias in the results obtained[76].

We apply the proposed methodology to a detailed dataset with unique characteristics. This dataset covers a banking system that went through a wave of mergers, thus constituting an ideal laboratory for estimating a counterfactual scenario. Our dataset allows for the investigation of the merger impact on corporate and household bank loans separately[77]. We are able to analyze the effects of mergers on the merged banks as well as on those banks outside the merging circles, taking into account endogenous changes in the post-merger market structure. Furthermore, we analyze the resulting changes in local competition by modeling the effects of changes in local market structure on the aggregate industry configuration.

There is a large literature on the gains banks obtain from merging (see Degryse et al., 2009). Berger et al. (1999) argue that there is consistent evidence

[76] The dangers of neglecting this issue in the analysis of different economic periods are extensively discussed in Lerner and Tufano (2011).

[77] Beck et al. (2009) provide evidence regarding the importance of analyzing household and firm loans separately.

that bank mergers increase market power, improve profit efficiency and allow for risk diversification, though the impact on cost efficiency is small on average. Focarelli et al. (2002) find that mergers increase return on equity, but they also lead to a rise in staff costs. In turn, they find that acquisitions generate a long-term reduction in lending, mainly for small firms, and a permanent decrease in bad quality loans, which positively affects long-run profitability. Focusing on European mergers, Altunbas and Marqués (2008) find that improvements in banks' performance subsequent to mergers are more significant if there are strategic similarities between the merging banks. Mergers and acquisitions also generate important changes in market structure and financial stability, as discussed in Adams et al., 2009, Berger et al., 2004, Cerasi et al., 2010, Craig and Santos, 1997, or in Gowrisankaran and Holmes, 2004). Some authors also find that mergers may enhance cost reduction and improve resource allocation. Moreover, mergers may generate informational gains, which improve banks' screening abilities and customer discrimination (see, for instance, Hauswald and Marquez, 2006, or Panetta et al., 2009). In turn, Beck et al. (2006) show that bank mergers may have implications for financial stability.

It is also important to assess the impact of bank mergers on customers with varying characteristics. Several authors conclude that bank mergers may negatively affect borrowers, most notably if they are small and medium size firms, dependent on bank funding and with a limited number of bank relationships. For instance, Bonaccorsi di Patti and Gobbi (2007) find that, for a sample of Italian firms, bank mergers have a negative effect on credit, particularly if the lending relationship comes to an end after the merger. This effect persists only during the three years after the merger. Still, this negative effect is not sufficient to generate a negative impact on firms' investment or cash-flow sensitivity. Other authors find mixed evidence regarding the impact of bank mergers. Also using a sample of Italian firms, Sapienza (2002) concludes that in-market mergers benefit borrowers if these mergers involve banks with limited market power. However, as the market share of the acquired bank increases, the efficiency gains are offset by an increase in market power, which may imply a decrease in loan supply, especially to small borrowers. In another study, Scott and Dunkelberg (2003) analyze the results of a survey on US firms and find that bank mergers do not affect loan supply or interest rates, even though there is some deterioration in non-price loan terms, such as fees for specific services. Degryse et al. (2011) find that the impact of a bank merger is more negative for smaller borrowers and for single relationship borrowers. Moreover, target bank borrowers should be more harmed by the merger than borrowers of the acquiring bank. Fraser et al. (2011) also provide evidence showing that large mergers generate highly negative wealth effects on borrowers. In contrast, Erel (2011) finds that bank mergers reduce loan spreads, most notably when the mergers generate cost savings. Finally, Karceski et al. (2005) argue that mergers may have impacts on borrowers beyond credit availability and interest rates. These authors show that mergers may in fact have important consequences on firm value, observing that borrowers of the acquiring banks usually benefit from the mergers, whereas firms that borrow from the target bank suffer an opposite impact[78, 79].

In the present chapter, we use a structural model of equilibrium in credit markets to analyze the impact of changes in market factors due to the merger wave. One of the most common approaches in the literature is to estimate the differential impact of mergers. Using the structural model, we are able to go further and estimate a counterfactual scenario for the post-merger period, thus going beyond the simple (and insufficient) comparison of variables before and after mergers occur, which is usually performed for the assessment of merger impact. Using this methodology, we compare the interest rate and credit flows

[78] There is less work done on the impact of bank mergers on depositors. There is some empirical evidence for Italian firms which suggests that bank mergers may have positive consequences for depositors in the long-run, even though there may be some negative effects in the short run (Focarelli and Panetta, 2003). However, Craig and Dinger (2009), using US data, obtain a different result, given that they do not observe any positive long-term effect of mergers on deposit interest rates. Their results are consistent with previous work done by Prager and Hannan (1998).

[79] For a more detailed review of the recent literature on the impact of bank mergers, see Degryse et al. (2009) and DeYoung et al. (2009).

in the post-merger equilibrium setup with the value of these variables under a counterfactual equilibrium. This counterfactual equilibrium is estimated using the after-merger exogenous environment under the pre-merger market structure.

As an alternative to structural estimation, a possibility would be to estimate a reduced-form treatment effects model. This would require comparing banks involved in mergers (treated) with those not involved (non-treated). However, given the magnitude and impact of the mergers analyzed, this empirical strategy would hardly lead to accurate estimates of the merger effects, as the changes in market structure and conduct originated by the mergers should have affected to some extent all banks, either directly or indirectly. Hence, our methodology is especially useful to analyze large mergers in small (and concentrated) banking systems.

The estimation of counterfactuals to assess the impacts of a merger may be considered an important policy tool. For instance, Ivaldi and Verboven (2005) emphasize that the evaluation of a merger from a policy perspective should not be based solely on a static comparative analysis, but should also consider dynamic effects and alternative merger scenarios. Berry and Pakes (1993) also argue that static models of equilibrium do not take into account the long-run reactions of merging and non-merging firms, thus generating misleading results. More recently, Lerner and Tufano (2011) show that the simple comparison of different economic periods suffers from serious endogeneity problems, stressing the need to develop a structured counterfactual approach to analyze what would have happened if a given event had not occurred. In an application to the airline industry, Peters (2006) demonstrates the importance of designing a counterfactual analysis to evaluate the impact of mergers, but is silent regarding the possibility of collusion or strategic interactions between firms. Berger et al. (1998) find empirical evidence that supports the view that the dynamic effects of mergers may generate results different from those obtained using static analysis. The authors identify a decrease in lending to small business after a merger, even though this static effect is largely offset by dynamic effects associated with changes in the focus of the merging banks or with the reaction of other banks. Nevertheless, these authors do not consider local changes induced by mergers, neither do they compare the impact on different institutional sectors[80].

Our paper contributes to the literature on merger impact in banking markets by presenting a counterfactual analysis, based on a structural model of equilibrium that clearly disentangles the effects of bank mergers on loan flows and interest rates and takes into account changes in market structure and

[80] Other papers have also analyzed local indicators of bank competition (see, for instance, Berger et al., 1995, and Berger et al., 1998).

conduct that may occur after the merger takes place. Our analysis is based on loan flows, as opposed to outstanding amounts, thus allowing us to better capture changes in credit markets over time. Moreover, the data used allow us to discriminate effects among corporate and household borrowers, and to simulate the counterfactual equilibrium to the mergers that occurred. This approach lends itself to the reporting of intuitive measures of merger impact upon the degree of competition in the market. The use of a counterfactual scenario becomes necessary, as mergers change the market structure underlying bank competition. This issue is important to stress, as virtually all banking merger studies rely on some exogenously treated market structure measure for the post merger configuration, even though the merger itself endogenously propagates the new equilibrium configuration.

We are able to make use of a significant change in market structure in the Portuguese banking market. Portugal is a small economy participating in the European Union, and joined the euro area at its inception. Like other European Union countries, it experienced a wave of mergers in the banking sector. The most significant changes occurred in 2000, with the merger of several financial institutions. The almost simultaneous nature of these mergers provides a natural break point in time, allowing us to define a pre- and a post-merger period. Hence, we divide the 1995-2002 period in two: the pre-merger

1995-1999 period and the post-merger 2000-2002 period[81]. Four out of the seven major financial groups were directly involved in those operations, either by selling or by acquiring at least one financial institution. In this chapter, we analyze two different products (credit to households and to firms), two different groups of institutions (those that are directly involved in the mergers and those that are not) and consider two different periods (pre- and post-mergers).

Several interesting findings emerge from our analysis. We find that the 2000 merger wave increased total credit granted and decreased interest rates. However, the analysis of aggregate credit flows hides important differences between institutional sectors. In fact, we find that the amount of credit flow granted to the household sector decreased, while the amount of credit granted to the corporate sector increased during the same period. The changes in credit flows affected both the banking groups involved in the mergers and the groups not involved. In fact, all financial institutions experienced an increase in the corporate credit sold following the mergers and a decrease in the interest rate charged. However, the banks directly involved in the merger recorded a larger increase in corporate credit than the banks that were not directly involved in

[81] Even though Portugal joined the euro area at its inception in 1st January 1999, the effects of the convergence process in credit markets were felt mainly during the 90s. As discussed in Antão et al. (2009), interest rates decreased gradually during the 90s due to this convergence process and, simultaneously, credit accelerated during this period. Hence, the effects of joining the euro area were gradual and not concentrated specifically around 1999.

the merger. The decline in credit granted to the household sector after the merger period, which was concentrated in banks not involved in the merger wave, suggests that households may be more sensitive to changes in local market competition. These results show that mergers may actually affect the degree of competition in the market, through the changes in the local market structure, to a larger extent than predicted by aggregate market analysis.

In sum, we observe that potential efficiency gains generated by the mergers seem to have been transmitted to customers through lower lending rates[82]. Moreover, access to credit improved significantly for firms after the mergers, though the same was not observed for households. When compared to the differential analysis usually implemented in the banking literature, the counterfactual estimation allows for a more precise and correct quantification of these impacts, while isolating changes in the exogenous environment from changes in endogenous market structure. The results obtained suggest that changes in banks' exogenous environment were behind most of the changes in interest rates and loan flows after the merger, particularly so for loans to households.

The chapter proceeds as follows. Section 5.2 develops the model of the equilibrium in the credit market. Section 5.3 describes the data and the major corporate changes in the banking system in 2000. Section 5.4 estimates the

[82] For a discussion on efficiency gains arising from bank mergers, see Sapienza (2002).

structural model of equilibrium in the credit market and Section 5.5 analyzes the impact of the merger wave. Section 5.6 presents some concluding remarks.

5.2 The Analytical Framework

5.2.1 Demand Equation

Given our purpose of assessing the market equilibrium effects of bank mergers, our approach to estimation has to rely on a minimum structure, such that alternative market equilibria can be computed. At the same time, the model needs to be parsimonious and flexible. Moreover, changes in competition should be analyzed at the most disaggregated level possible. Even though there is no information on the local market operations of each bank, we do have information on the location of branches and on characteristics of local markets (such as population), thus allowing us to consider differences in local bank competition. In fact, as local market competition certainly depends on the number and location of branches, the relative position of the branch network of each bank does affect the demand faced by the bank, and thus own and rival banks branch densities are considered in our model. The branch density is commonly used in the empirical literature on local banking competition (see, for instance, Degryse and Ongena, 2005). We consider that rivalry between banks is relevant on the choice of interest rates. Finally, economy-wide variables should influence demand and must be included as demand-side controls.

Since our unit of observation is the bank, we consider the total market demand L_{it} directed at each bank (i), during a quarter (t). Loan demand, L_{it}, is measured by loan flows, rather than outstanding loans, thus capturing loan demand in each quarter. Loan demand depends on two different sets of variables: economy-wide variables that simultaneously affect all banks (V_t) and bank-specific determinants (S_{it})[83]:

$$L_{it} = V_t \; S_{it}$$

The set of variables V_t includes the aggregate average interest rate on new loans granted in the country in quarter t, r_t, and Z_t which refers to overall macroeconomic conditions (captured by the quarterly GDP). The vector V_t is thus given by:

$$V_t = A_{0v} r_t^{\alpha_1} Z_t^{\alpha_2}$$

where A_{0v} is a constant, and α_1 and α_2 are parameters to be estimated.

The bank specific variables, S_{it}, include the number of branches of a bank

[83] See Kim and Vale (2001) for further details.

and of its rivals, B_{it} and $B_{-it} = (B_t - B_{it})$, respectively. The bank-specific interest rate, r_{it}, should also be a determinant of the loan demand directed at each bank. It is important to note that in each period, the decision variable r_{it} is the average interest rate that bank i charges on new loans granted during quarter t, not the average interest rate on existing loans. The overall demand directed at bank i is also determined by the level of competition the bank faces in the local markets in which it is active, as well as by the relative size of such markets. In fact, for a given number of branches, different locations can imply significant differences in demand generated. Therefore, we include a set of local market competition variables X_{it}.

The vector of bank-level determinants is thus given by:

$$S_{it} = A_{0s} B_{it}^{\phi_1} B_{-it}^{\phi_2} r_{it}^{\phi_3} X_{it}^{\phi_4}$$

where A_{0s} is a constant and ϕ_1, ϕ_2, ϕ_3 and ϕ_4, are parameters to be estimated.

Pooling all variables together, the demand equation we estimate is:

$$\ln L_{it} = \alpha_0 + \alpha_i + \alpha_1 \ln r_t + \alpha_2 \ln Z_t + \phi_1 \ln B_{it} + \phi_2 \ln B_{-it} + \phi_3 \ln r_{it} + \phi_4 \ln X_{it} + \varepsilon_{it} \tag{5.1}$$

where α_0 is a constant and α_i are bank fixed effects.

In equation (5.1), the vector of local market characteristics X_{it} consists of:

$$POP_{it} = \sum_{k=1...K} POP_{ikt} \frac{B_{ikt}}{B_{it}}$$
$$LC_{it} = \sum_{k=1...K} \left(\frac{B_{kt} - B_{ikt}}{B_{kt}} \frac{B_{ikt}}{B_{it}} \right)^2$$

where the sum is performed for all the k districts in the country[84].

The variables capturing local market characteristics deserve some further justification. The first one, $POP_{it,}$ is a measure of the importance of each market to bank i in period t, taking into account the population (POP) in that market. It is defined as the proportion of branches each bank has in market k is weighted by the population in that market. Thus, banks that have a higher proportion of branches in more heavily populated areas will have, ceteris paribus, a higher demand for their loans.

The second measure, LC_{it}, attempts to capture not a rough indicator of the level of potential demand in each market, but the intensity of local competition. The basic element is the share of (branch) competition faced by bank i in market k. This is given by the share of rival banks in the total number of branches in market k, weighted by the importance of market k, branch-wise, to bank i. This index can accommodate the differences involved in having

[84] There are 18 districts in Portugal.

branches in markets where other banks have no branches relative to crowded markets.[85]

5.2.2 The Bank's Problem

After setting the demand function faced by each bank, we turn now to the supply side of the market. The profit function of a bank relevant for our analysis, which focuses on the loan market, can be simply stated as interest rate income less marginal costs multiplied by total (new) loan demand in each period. Marginal costs include the opportunity cost of financial funds.

The relevant (short-run) decision variable of bank i is its interest rate. To account for possible strategic interactions among banks belonging to different economic groups, we take a simple approach, assuming that they take into consideration the impact they have on the profits of other banks. Under perfect collusion (or joint management) banks would maximize joint profits, while under perfectly independent behavior each would maximize own profits. Thus, this approach accommodates intermediate situations by the introduction of a single parameter, which measures to what extent a bank considers the impact of its decisions on the profits of other banks[86].

The bank's problem is to maximize profits using the interest rate as the

[85] A similar index can be found in Barros (1999).
[86] For a similar approach, see Barros (1999).

control variable:

$$\max_{r_{it}} \Pi_{it} = L_{it}(r_{it} - c_{it}) + \sum_{j \neq i} \lambda_{ij} L_{jt} \left(r_{jt} - c_{jt} \right)$$

where j represents all remaining banks and c_{it} is a measure of weighted funding costs, taking into account deposits and interbank funding. Parameters λ_{ij} are the competition factor that accounts for the effect of bank j on bank i's objective function. If $\lambda_{ij} = 1$, there is collusion, whereas if $\lambda_{ij} = 0$ banks maximize profits independently.

Using the demand equation defined in the previous section, it becomes straightforward to characterize the optimal interest rate choice taken by bank i. The first order condition is:

$$0 = \frac{\partial \Pi_{it}}{\partial r_{it}} = L_{it} + \frac{\partial L_{it}}{\partial r_{it}}(r_{it} - c_{it}) + \sum_{j \neq i} \lambda_{ij} \frac{\partial L_{jt}}{\partial r_{it}} \left(r_{jt} - c_{jt} \right)$$

and from specification (5.1), we have:

$$\begin{aligned}
\frac{\partial L_{it}}{\partial r_{it}} &= \frac{\phi_3}{r_{it}} L_{it} \\
\frac{\partial L_{jt}}{\partial r_{it}} &= \left[\frac{\partial L_{jt}}{\partial r_t} \right] \left[\frac{\partial r_t}{\partial r_{it}} \right] = \left[\alpha_1 \frac{1}{r_t} L_{jt} \right] \left[\frac{1}{n_t} \frac{1}{r_{it}} r_t \right] = \alpha_1 \frac{1}{n_t} \frac{1}{r_{it}} L_{jt}
\end{aligned}$$

where we have used the fact that $(1 + r_t) = \left[\Pi_{i=1}^{n} \left(1 + r_{it} \right) \right]^{1/n_t}$ and n_t is the total number of banks in quarter t.

Simplification allows us to write the first-order-condition as:

$$0 = L_{it} + \phi_3 L_{it} \frac{r_{it} - c_{it}}{r_{it}} + \sum_{j \neq i} \lambda_{ij} \alpha_1 \frac{1}{n_t} L_{jt} \frac{r_{jt} - c_{jt}}{r_{it}}$$

For estimation purposes, it becomes useful to solve the equation with respect to the interest rate r_{it} and estimate the following equation:

$$r_{it} = \frac{\phi_3}{1 + \phi_3} c_{it} + \sum_{j \neq i} \lambda_{ij} \frac{\alpha_1}{-\phi_3 - 1} \frac{1}{n_t} \frac{L_{jt}}{L_{it}} (r_{jt} - c_{jt}) + \beta_i + \upsilon_{it} \tag{5.2}$$

where β_i are bank fixed effects and υ_{it} are estimation errors.

5.2.3 The System of Equations

Together, the system of equations (5.1) and (5.2) characterize the equilibrium in the credit market. As discussed above, the strategic effects between bank i and its j rivals are captured by the group of parameters λ_{ij}. As the number of parameters implied by λ_{ij} is potentially quite large, restrictions on possible values will be imposed during estimation. Hence, in order to simplify the empirical estimation, we will reduce the number of strategic effects and consider the interaction of bank i with its main rival, which is defined to be the financial institution with the lowest interest rate during the quarter, $R\min_{it}$.[87] As a consequence, the system to estimate is given by:

$$\begin{cases} \ln L_{it} = \alpha_0 + \alpha_i + \alpha_1 \ln r_t + \alpha_2 \ln Z_t + \phi_1 \ln B_{it} + \phi_2 \ln B_{-it} + \phi_3 \ln r_{it} + \\ +\phi_{41} POP_{it} + \phi_{42} LC_{it} + \varepsilon_{it} \\ \\ r_{it} = \beta_0 + \beta_1 c_{it} + \beta_2 R\min_{it} + \beta_i + \upsilon_{it} \\ \\ \beta_1 = \frac{\phi_3}{1+\phi_3} \\ \\ R\min_{it} = Min_{r_{jt}} \left[\frac{1}{n_t} \frac{L_{jt}}{L_{it}} (r_{jt} - c_{jt}) \right] \end{cases} \tag{5.3}$$

The system (5.3) highlights the nonlinear constraint involving the parameters β_1 and ϕ_3, representing a link between equations (5.1) and (5.2).

[87] We have tried different strategic effects and the results do not change significantly. For instance, we have considered (i) defining the main rival as the bank that has granted more credit during the quarter ($Xmax_{it}$), (ii) the bank with the closest loan flow in each quarter, (iii) the interaction of the five main rivals, (iv) the average of the interaction of the five main rivals $\text{Xmax}_{it} = 1/5 \sum_{j=1,\ldots,5} X\max_{jt}$ or (v) the interactions given by: $Xmax_{it} = (\frac{1}{n_t}) \sum_{i=1,..5} \frac{L\max_i}{Lit} (r\max_i - c_{jt})$.

5.3 The Data

The final dataset is the result of merging three different sources of data. The first dataset includes information on the branches' location. The second dataset includes unique interest rate and credit data, which allows distinguishing between the household and the corporate sectors. The third database gathers the regional characterization. The final dataset consists of quarterly data from the first quarter of 1995 to the third quarter of 2002 and each observation corresponds to a bank in each quarter.

Regarding branch location, the data are collected by the Banking Supervision Department at Banco de Portugal. Whenever a bank establishes a branch, it is required to report this event to the supervisor within a period of three months. The same time period is set for a branch change of address, closing or other major change.

The data on credit and interest rate is collected from the Monetary and Financial Statistics (MFS) of Banco de Portugal. The MFS are a monthly mandatory survey sent to all financial institutions operating in the country and includes information on end-of-period stocks and flows of credit granted to households and to non-financial corporations[88]. Data on interest rates are

[88] For further details on the Monetary and Financial Statistics, please see http://www.bportugal.pt/en-US/Estatisticas/Dominios%20Estatisticos/Pages/EstatisticasMonetariaseFinanceiras.aspx

based on the flows of new credit granted. There was a major revision in interest rate statistics at the end of 2002, with the purpose of harmonizing methodologies within the Eurosystem, which prevents the use of more recent data. In fact, from 2003 onwards, interest rate statistics began to be estimated using a sample of representative banks, instead of using the whole universe of banking institutions, as before. Hence, there are several banks (including small banks belonging to the seven largest banking groups) for which there is no interest rate data after end-2002. Nevertheless, a longer estimation period would probably not be adequate, given that the effects of mergers should be more strongly and clearly captured in the years immediately after these mergers[89]. Moreover, it would be a very strong assumption to require that the pre-merger equilibrium holds for many years after the merger wave, as changes in economic and financial variables should also shape this equilibrium.

Finally, we further collected data on the demographic characteristics of the districts from Statistics Portugal, including total population by municipality.

or http://www.ecb.int/ecb/legal/1005/1021/html/index.en.html.

[89] For instance, Berger et al. (1998) consider that the dynamic effects of bank mergers should be analyzed in the three years following the merger.

5.3.1 Description of the 2000 Merger Wave

During the 1995 to 2002 sample period, the Portuguese financial system experienced several restructuring processes. Among the main corporate changes, we highlight the most significant ones:

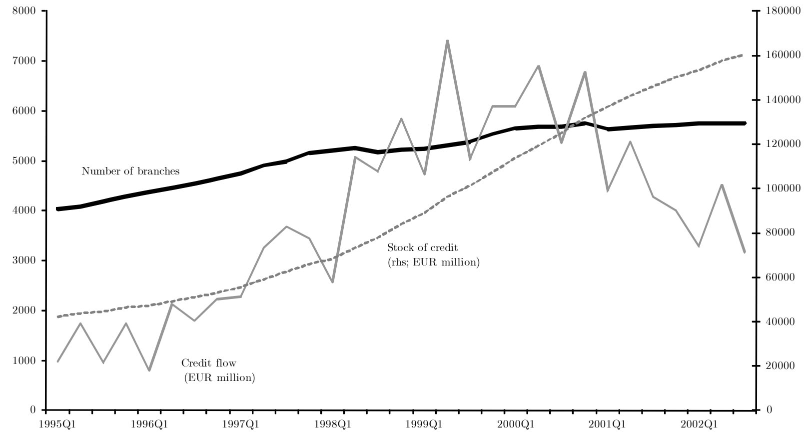
Date	*Event*
January 1996	*Banco Português de Investimento* (BPI) buys *Banco Borges & Irmão* (BBI) and *Banco Fonsecas e Burnay* (BFB).
December 1997	*Banco Comercial de Macau* (BCM) changes to *Expresso Atlantico.*
September 1998	Merger between BBI, *Banco Fomento e Exterior* (BFE) and BFB. The new institution is named as BBPI.
March 2000	The group *Banco Pinto e Sotto Mayor* (BPSM), which included the banks BPSM, *Banco Totta e Sotto Mayor Inv* (BTSM Inv), *Banco Totta e Açores* (BTA) and *Credito Predial Português* (CPP), is extinguished.
March 2000	The bank BPSM is bought by *Banco Comercial Português* (BCP).
March 2000	BTSM Inv is acquired by *Caixa Geral de Depósitos* (CGD).
March 2000	CPP is acquired by BTA.
September 2000	Santander buys BTA.

Among the main events, the ones occurred in 2000 are by far the most important, as they involved major banks as well as major financial groups. These are universal banks operating in most retail market segments throughout the country. Among the seven major financial groups, four were directly involved either by selling a financial institution or by acquiring one, thus generating profound changes in the structure of the Portuguese banking market. Due to the significant changes occurring in 2000, we may distinguish between specific characteristics of the pre-2000 period, which we designate as the pre-merger period (comprehending the years 1995-1999), and specific characteristics of the after-2000 period, which we denominate the post-merger period (including the years 2000-2002).

To better understand the changes occurring in the credit market during 2000 we analyze the evolution of the stock of credit and total number of branches in the country during the 1995-2002 period. The pattern is presented in Figure 5.1. The figure reveals that credit flows seem to peak at mid-1999, while the total number of branches increased more significantly between 1995 and 1998. Figure 5.1 also reveals a decelerating trend in the number of branches following the important consolidation move in 2000.

An inspection of the aggregate numbers in Figure 5.1 suggests that the merger and acquisition activity in 2000 did not significantly affect the total

Figure 5.1: Credit and total number of branches



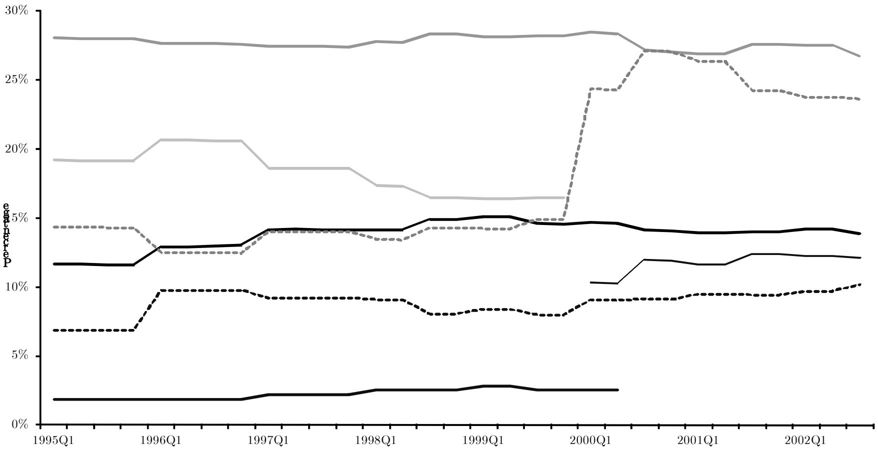
Notes: The stock of credit and the credit flow reported are aggregate values from the Monetary and Financial Statistics, Banco de Portugal.

credit figures but that is not necessarily so for the within group composition. In Figure 5.2 we are able to take a closer look at the corporate changes and compute the market shares of the total stock of credit for the main financial groups during the 1995-2002 period. We observe that the 2000 merger wave significantly changed the market share of some groups. Moreover, as illustrated in Figure 5.3, the banking groups involved in the 2000 merger wave experienced a larger gain in market shares than the remaining banks[90].

We also observe that after the merger wave there was some increase in the

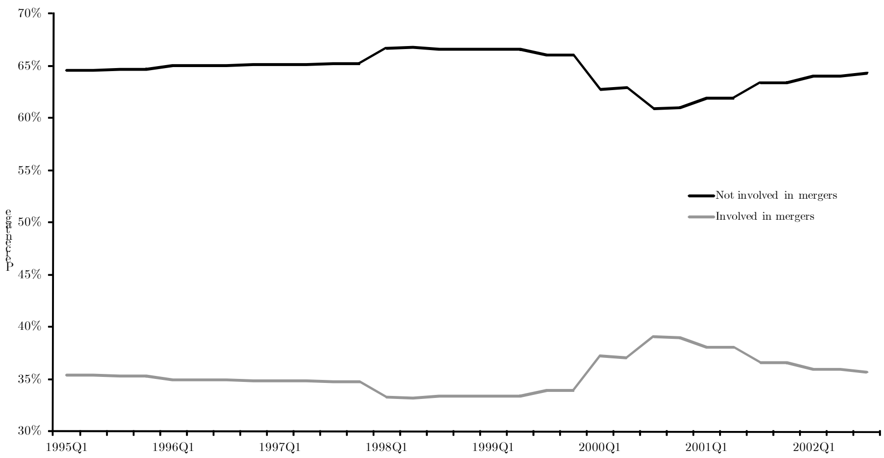
[90] We consider that both the acquiring and the acquired banking groups are involved in the merger.

Figure 5.2: Market shares of the major financial groups



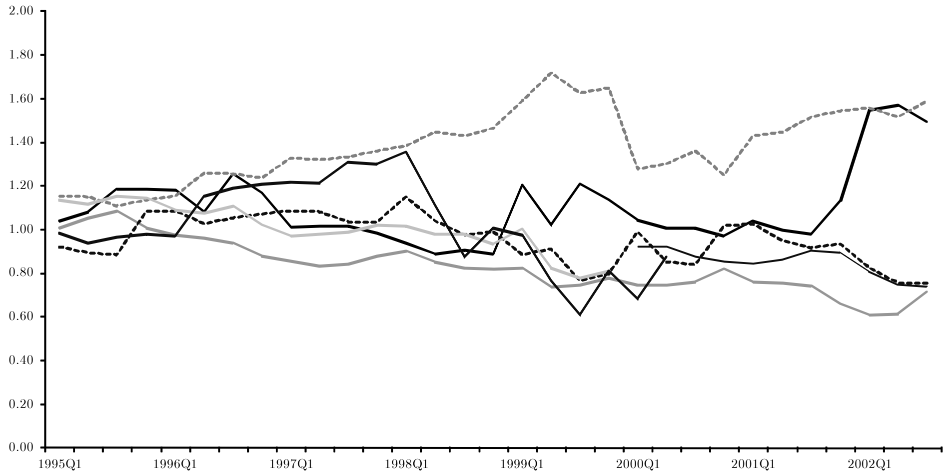
Notes: Market shares are computed by taking into account the total outstanding amount of credit. Banks were grouped into 8 major groups: the 7 largest banking groups in the banking system, plus one additional group including all other small banks. Only the 7 largest banking groups are considered in this figure. Each line represents a different group.

Figure 5.3: Market shares of the groups involved in mergers and of the remaining banks



Notes: Market shares are computed by taking into account the total outstanding amount of credit. The group of financial institutions directly involved in the merger includes institutions belonging to financial groups that have acquired or sold a financial institution to a different financial group in 2000. The small banks not belonging to any large banking group are considered in the set of banks not directly involved in the mergers.

Figure 5.4: Relative interest rates of the major financial groups

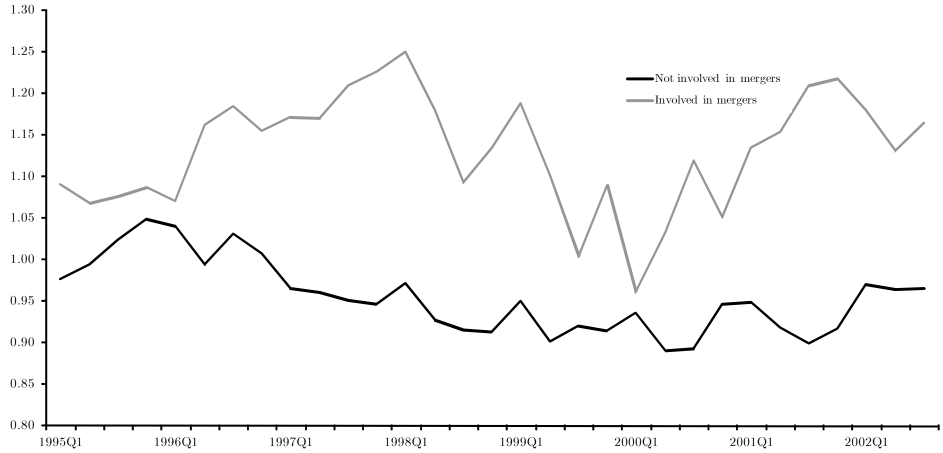


Notes: The relative interest rates are computed as the average rate on new loans granted by each banking group relative to the average rate on all new loans granted in each quarter. Banks were grouped into 8 major groups: the 7 largest banking groups in the banking system, plus one additional group including all other small banks. Only the 7 largest banking groups are considered in this figure. Each line represents a different group.

dispersion of interest rates of the larger banking groups (Figure 5.4). This heightened dispersion was mostly due to a relative increase in interest rates offered by the groups directly involved in the 2000 merger wave (Figure 5.5).

All this evidence suggests that the significant changes occurring in 2000 may have had important consequences in the credit market, namely on credit granted, interest rates charged and on the strategic effects among the financial players. This chapter analyzes those changes.

Figure 5.5: Relative interest rates of the groups involved in mergers and of the remaining banks



Notes: The relative interest rates are computed as the average rate on new loans granted by each banking group relative to the average rate on all new loans granted in each quarter. The group of financial institutions directly involved in the merger includes institutions belonging to financial groups that have acquired or sold a financial institution to a different financial group in 2000. The small banks not belonging to any large banking group are considered in the set of banks not directly involved in the mergers.

5.3.2 Summary Statistics

Overall, there are 71 banks in the dataset that are in operation for at least one quarter during the sample period. Banks are grouped in 8 major financial groups: we consider the seven most important financial groups that include 26 banks and one additional group including the remaining banks in the sample[91]. Four of these banking groups were directly involved in the 2000 merger wave.

Table 5.1 presents the summary statistics of our sample for the stock of credit, flows and other variables for three different groups of banks: i) the four large banking groups involved in the merger wave, ii) the three large banking groups not involved in the mergers, and iii) the remaining banks that were not involved in the merger wave. The average credit market share of a bank belonging to the group of banks engaged in mergers is 3.4 percent, while the large banks that do not belong to this group have on average 6.7 percent of the total stock of credit. In turn, the smaller banks not involved in mergers have only, on average, 0.6 percent of the credit market. Statistical tests show that these banks are indeed quite different. This evidence highlights the importance of treating these banks separately and, hence, they will be excluded from regression analysis.

[91] As shown by Park and Pennacchi (2009), bank mergers affect differently large and small banks, hence justifying analyzing them separately.

Table 5.1 - Summary statistics

	Banks involved in mergers				
	Obs	Mean	Std. Dev.	Min	Max
Stock of credit					
Total stock of credit	323	2751	5134	1.5	31866
Number of branches	323	175	249	1	1312
Market share (total credit)	323	3.4	4	0.0	26.1
Flow of credit					
Total credit flow	323	2268	6064	0.2	39776
Credit flow (households)	323	318	761	0	5769
Credit flow (corporate sector)	323	1950	5335	0	35655
Interest rates					
Interest rate	323	11.1	5	3.2	25.7
Interest rate (household credit)	287	13.2	5	3.2	25.7
Interest rate (corporate sector credit)	264	9.9	4	3.1	23.5
Interbank market rate	323	5.2	2	2.4	9.1
Bank specific and demographic variables					
ROA	323	0.003	0.0	-0.1	0.03
LC	323	0.3	0.3	0.1	1.0
POP	323	14.0	3.8	9.4	21.4

	Large banks not involved in mergers						Other banks not involved in mergers					
	Obs	Mean	Std. Dev.	Min	Max	Mean tests	Obs	Mean	Std. Dev.	Min	Max	Mean tests
Stock of credit												
Total stock of credit	232	5422	7270	0.04	37014	***	791	419	580	0.24	3268	***
Number of branches	232	242	229	1	786	***	791	26	44	1	217	***
Market share (total credit)	232	6.7	8	0.0	27.4	***	791	0.6	1	0.0	3.9	***
Flow of credit												
Total credit flow	232	1903	2866	0	16420		791	314	555	0	3514	***
Credit flow (households)	232	401	567	0	2750		791	41	78	0	437	***
Credit flow (corporate sector)	232	1502	2341	0	13812		791	273	496	0	3116	***
Interest rates												
Interest rate	232	9.2	4	3.8	20.0	***	791	8.5	4	2.6	23.6	***
Interest rate (household credit)	213	10.4	4	3.2	20.0	***	622	10.2	5	1.5	28.0	***
Interest rate (corporate sector credit)	226	9.3	4	3.8	18.8		736	7.9	3	2.6	22.3	***
Interbank market rate	232	5.0	2	2.4	9.1		791	4.9	2	2.4	9.1	**
Bank specific and demographic variables												
ROA	232	0.003	0.0	-0.1	0.02		791	0.001	0.0	-0.3	0.04	
LC	232	0.3	0.3	0.1	1.0	**	791	0.5	0.3	0.1	1.0	***
POP	232	13.0	3.7	2.4	21.4	***	791	15.0	5.1	2.5	21.4	***

Notes: The group of financial institutions directly involved in the merger includes institutions belonging to financial groups that have acquired or sold a financial institution to a different financial group in 2000. All credit values are in Eur million. Market shares are computed by taking into account the total outstanding amount of credit and are displayed as percentages. Interest rates are annualized and refer to new loans granted in each quarter. ROA is the return on assets of each bank, LC is a measure of local competition and POP is a measure of the importance of each market to bank i in period t. LC and POP are defined in Section 2.1. The columns "mean tests" refer to mean comparison tests between each group and the group of banks involved in the mergers. *** significant at 1%, ** significant at 5%, * significant at 10%.

The average interest rate on the total credit flow charged by the banks involved in mergers is 11.1 percent (9.2 percent for the other large banks and 8.5 for the smaller banks). The household market experiences higher interest rates (13.2, 10.4 and 10.2 percent for the groups of banks under analysis) than the corporate sector (9.9, 9.3 and 7.9 percent, respectively)[92].

These statistics refer to the entire sample period. We will analyze how the merger wave affected credit flows and interest rates, both for households and for firms.

5.4 Analysis of Equilibrium in the Credit Market

Table 5.2 presents the results of the estimation of the system (5.3). The model is estimated for quarterly data and covers the 1995-2002 period. Estimating the model for the full period allows for a characterization of market structure, which can be useful as a benchmark to assess the impact of mergers. Columns (1) - (2) characterize the equilibrium for the total credit granted, aggregating household and corporate credit, and columns (3) - (4) and (5) - (6) correspond to the estimations for the household and corporate sectors, respectively. It should be noted that, in this setting, we are able to differentiate banking output

[92] Most of the banks in the sample operate in both the household and the corporate credit markets, even though some small banks display null credit flows in one of these segments in some quarters. All banks considered grant credit to households and only two small banks never grant credit to firms during the entire sample period.

into household and firm loans without making any assumptions regarding their complementarity or substitutability, given that these are two different and independent markets. This implies null cross-elasticities of demand between these markets, given that, by definition, customers cannot switch between these two markets. Thus, specifying linear demand functions should not inflict problems that would exist in markets where these cross-elasticities vary in response to different strategies[93].

[93] Berg and Kim (1998) empirically document such separability in the Norwegian market and present a discussion on cross-market interactions when banks produce multiple outputs.

Table 5.2 - Characterization of the determinants of credit flows and interest rates

	Total credit flows		Households		Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
	System of equations		System of equations		System of equations	
	ln(Credit)	rit	ln(Credit)	rit	ln(Credit)	rit
ln(number of branches)	1.250 ***		0.884 **		1.658 ***	
	(3.98)		(2.48)		(3.53)	
ln(number of branches other banks)	-0.863		0.475		-3.076 ***	
	-(1.23)		(0.69)		-(3.21)	
$\ln(r_t)$	-0.417		-0.119		-0.265	
	-(1.41)		-(0.30)		-(0.54)	
$\ln(r_{it})$	-0.194 ***		-1.155 ***		-1.197 ***	
	-		-		-	
GDP	0.031		0.075 ***		0.008	
	(1.46)		(3.08)		(0.23)	
POP	0.069		0.013		-0.199 *	
	(0.88)		(0.12)		-(1.70)	
LC	8.277 ***		5.356 *		20.126 ***	
	(3.62)		(1.94)		(6.23)	
c_{it}		1.198 ***		1.210 ***		1.213 ***
		(27.05)		(23.11)		(23.46)
Rmin		-1.683		-0.110		0.132 ***
		-(0.15)		-(0.09)		(3.51)
constant	5.247	5.279 ***	-3.412	6.304 ***	25.161 ***	5.419 ***
	(0.81)	(7.57)	-(0.52)	(7.89)	(2.73)	(7.04)
Lambda		-3.3		0.1		-0.1
Standard error		-39.3		-3.1		-0.1
$H_0: \lambda = 0$		0.88		0.93		0.59
$H_0: \lambda = 1$		0.85		0.60		0.00
Observations	562	562	507	507	496	496

Notes: All regressions include banks' fixed effects and robust standard errors. Robust t statistics are presented in parentheses. * significant at 10%; ** significant at 5%; *** signficant at 1%. The estimations are performed for quarterly data during the 1995-2002 period. Estimation is based on a seemingly unrelated (SUR) model. The interest rates refer to the new loans granted in each quarter. LC is a measure of local competition and POP is a measure of the importance of each market to bank i in period t. LC and POP are defined in Section 2.1. Cit is a measure of weighted funding costs, taking into account deposits and interbank funding. Rmin is a variable that measures the strategic interaction between banks, being defined as Rmin = (1/nbanks) * Ljt / Lit * (rjt - cjt), where Ljt and rjt are, respectively, the loan flow and the interest rates of each banks' rival, defined as that with the lowest interest rate in that quarter, in each market segment.

The t statistics for the coefficient associated with ln(rit) in columns (1), (3) and (5) are omitted, as this coefficient is determined by a constraint in the model. The lower number of observations in the regressions for households and firms is due to the fact that some small banks show null credit flows in one of these market segments in some quarters (two small banks never grant credit to firms during the entire sample period). Lambda reflects the effect of the rival banks on the profit maximization function of each bank and is derived from a combination of the estimated coefficients, resulting from the model.

The system of equations (5.3) is estimated using a seemingly unrelated (SUR) model, which allows for cross-equations correlation of the residuals. All regressions are estimated using banks' fixed effects and robust standard errors[94].

Looking at the results for the aggregated credit flows, in columns (1) - (2), we observe that the total number of branches is positively and significantly related to the logarithm of total credit granted, indicating that local branching arrangements are an important factor in liquidity provision[95]. We obtain an estimate for ϕ_1 equal to 1.25, with a t-statistic of 3.98. This means that a small increase in the number of bank branches had significant effects on the loan demand faced by each bank during the period analyzed.

In addition, the interest rate charged by the bank is negatively related to the total credit granted[96]. As expected, the interest rate charged by the bank i, r_{it}, is strongly and positively related to banks' funding costs, c_{it}. The

[94] For robustness purposes, banking group fixed effects were also included in the regressions, to take into account possible similarities or synergies between financial institutions integrated in the same banking group. The results are broadly consistent and are available upon request. Nevertheless, the value added by these additional fixed effects is marginal and implies an important loss of the degrees of freedom used in the estimations.

[95] In a recent paper, Corvoisier and Gropp (2009) argue that the widespread use of web-based banking platforms should have decreased sunk costs and increased contestability in retail banking, as establishing branches became less important. Nevertheless, the authors find that even though this hypothesis may be true for time and saving deposits, it does not hold for small business loans, where establishing a branching network with local connections is still important.

[96] In the table, we omit the t-stats for this coefficient in columns (1), (3) and (5), as this coefficient is determined by the constraint in system (5.3).

estimate for the coefficient β_1 is 1.20, with a t-statistic of 27.05. Hence, when banks' funding costs increase or decrease, the change in loan rates charged to customers is proportionally more significant.

Although columns (1) and (2) allow to identify the determinants of the credit and interest rates charged by the bank, the analysis for these aggregate credit flows smoothes important idiosyncratic characteristics of the determinants of the household and corporate sectors credit markets. Columns (3) and (4) present the results for system (5.3) for the household sector and columns (5) and (6) present a similar analysis for the corporate sector. The distinction across these institutional sectors highlights important differences in these markets, thus justifying a disaggregate specification rather than treating the credit market as a homogeneous market[97].

We observe that the banks' own number of branches positively influences credit granted, both to households and to firms (the estimated coefficients are 0.88 and 1.66, respectively). In turn, the number of branches of the remaining banks is not significantly correlated with credit granted to households, as illustrated in column (3), while it has a negative and significant impact on credit supplied to the corporate sector (column (5)).

[97] The lower number of observations in the regressions for households and firms is due to the fact that some small banks show null credit flows in one of these market segments in some quarters, as discussed in Section 5.3.2. Moreover, two small banks never grant credit to firms during the entire sample period.

Looking at the macro determinants, Table 5.2 reveals that the impact of the GDP level on credit granted is positive for both credit markets. Given that GDP reflects changes in global macroeconomic conditions and also changing industry risk, this result confirms the usually observed pro-cyclicality of liquidity provision[98]. However, this impact is statistically significant only for credit to households. Moreover, local branch competition has a positive impact on the credit flow. This impact is fourfold larger in the corporate than in the household sector[99].

The evidence on strategic behavior, measured by the coordination parameter λ, suggests that there is no collusion between banks, as λ is always less than one. The statistical tests on these parameters show that we can reject the hypothesis of perfect collusion ($\lambda = 1$) in the corporate credit market, thus suggesting that banks behave competitively in this market. However, for households we cannot rule out either the hypothesis of perfect collusion ($\lambda = 1$) or perfect competition ($\lambda = 0$). These results are consistent with previous evidence obtained by Berg and Kim (1998), who argue that the mobility of customers in the corporate market is stronger than in other markets, thus

[98] Controlling for GDP should capture the most relevant time fixed effects. To mitigate concerns about potential cointegration issues, we also considered the GDP growth rate, having obtained broadly similar results.

[99] The estimated coefficient ϕ_{42} is 5.36 for households (with a t-statistic of 1.94) and 20.13 for firms (with a t-statistic of 6.23).

generating more competitive behaviors by banks. More recently, Degryse et al. (2011) show that firms may benefit from switching banks after mergers occur, what is related to banks' competitive strategies.

Having analyzed the determinants of credit flow and interest rates for the household and corporate markets, we can now determine how these parameters change following bank mergers.

5.5 The Impact of the Merger Wave

This section analyzes the impact of the 2000 merger wave on the determinants of credit flows and interest rates. On the one hand, we are interested on the impact of the merger wave on the credit flow and interest rates charged and, on the other hand, we aim at determining how the merger has affected local branch competition and coordination moves in the banking industry.

For illustration purposes, we begin by estimating the differential impact of the merger wave, given that this is one of the most common approaches in the literature (see for example Erel, 2011, Focarelli and Panetta, 2003, or Sapienza, 2002). However, this reduced form differential analysis suffers from several drawbacks. In fact, this analysis does not take into account changes in market structure and conduct. In our opinion using a Herfindahl Hirschman Index should not be sufficient to adequately capture changes in market power resulting from mergers, as this measure is endogenous and may reflect other market dynamics. In fact, the magnitude of the merger wave should generate changes in the interaction between banks and possibly also in consumer preferences. Given these changes, the differential analysis, usually conducted in the literature, may lead to biased and incorrect estimates of the merger impact. Hence, we propose a new methodology for the comparison between the pre- and post-merger periods, through the estimation of a *counterfactual*. We explicitly consider that the merger wave might have generated a new setup in credit markets in the post-merger period. In this estimation we combine the pre-merger equilibrium setup with the post-merger observed environment to answer the *"what if"* question.

5.5.1 The Differential Impact of the Merger Wave

Taking into account one of the most common approaches used to assess the impact of mergers, we compute the differential impact of the merger wave on the equilibrium in the credit market. In particular, we analyze how variables such as the strategic behavior and local competition change after the merger. In order to pursue this objective, we consider a dummy variable $AFTER$ that has value one if the quarter is in year 2000 or after, and zero otherwise, and run a modified empirical model of (5.3)[100]:

$$\begin{cases} \ln L_{it} = \alpha_0 + \alpha_i + \alpha_{01} AFTER + \alpha_1 \ln r_t + \alpha_2 \ln Z_t + \phi_1 \ln B_{it} + \phi_2 \ln B_{-it} + \phi_3 \ln r_{it} + \\ +\phi_{41} POP_{it} + \phi_{42} LC_{it} + \phi_{43} LC_{it} * AFTER + \varepsilon_{it} \\ \\ r_{it} = \beta_0 + \beta_{01} AFTER + \beta_1 c_{it} + \beta_2 R\min_{it} + \beta_3 R\min_{it} * AFTER + \beta_i + \upsilon_{it} \\ \\ \beta_1 = \frac{\phi_3}{1+\phi_3} \\ \\ R\min_{it} = Min_{r_{jt}} \left[\frac{1}{n_t} \frac{L_{jt}}{L_{it}} (r_{jt} - c_{jt}) \right] \end{cases} \tag{5.4}$$

In this model, the coefficient α_{01} and β_{01} capture possible changes in the level of credit flow and of interest rates after the merger wave and ϕ_{43} considers the difference in the impact of the local branch competition on the quarterly credit flow following the 2000 merger with respect to the impact during the pre-merger period. Using the coefficient β_3 and equation (5.2) we can compute a similar differential effect for the strategic interaction, λ, which we name λ_{after}.

In Section 5.4 we assumed that the coefficients are time-invariant and thus

[100] The choice of the year 2000 is motivated by the large number of mergers observed, some of which involving some of the largest banks. As illustrated in section 5.3.1, these mergers had a substantial impact on market structure.

not affected by the merger wave. Hence, if any of these additional variables is significant, the results presented in Section 5.4 are inaccurate. In this subsection we will test the stability of these coefficients.

The results for the differential impact are presented in Table 5.3. Columns (1) - (2) present the analysis for the total credit flow (household plus corporate credit) and columns (3) - (4) and (5) - (6) present the results for the household and corporate sectors, respectively.

Table 5.3 - Analysis of the differential impact of the merger wave

	Total credit flows		Households		Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
	System of equations		System of equations		System of equations	
	ln(Credit)	rit	ln(Credit)	rit	ln(Credit)	rit
AFTER	0.343 **	-1.628 ***	-0.471 **	-2.003 ***	0.971 ***	-1.939 ***
	(2.09)	-(8.07)	-(3.01)	-(8.22)	(4.48)	-(8.40)
ln(number of branches)	0.974 ***		1.052 ***		1.168 **	
	(3.07)		(2.89)		(2.50)	
ln(number of branches other banks	-0.745		0.774		-3.337 ***	
	-(1.05)		(1.13)		-(3.56)	
$\ln(r_t)$	-0.133		0.343		-0.545	
	-(0.38)		(0.81)		-(1.04)	
$\ln(r_{it})$	-0.310 ***		-1.064 ***		-1.268 ***	
	-		-		-	
GDP	0.041		0.130 ***		-0.045	
	(1.37)		(4.01)		-(0.91)	
POP	0.130 *		-0.023		-0.213 *	
	(1.65)		-(0.21)		-(1.87)	
LC	6.066 ***		6.559 **		17.389 ***	
	(2.63)		(2.31)		(5.46)	
LC*AFTER	-1.021 ***		0.462		-2.289 ***	
	-(4.02)		(1.47)		-(5.21)	
c_{it}		1.046 ***		1.036 ***		1.068 ***
		(22.71)		(19.30)		(20.68)
Rmin		-15.475		-1.147		0.622 ***
		-(1.34)		-(1.01)		(4.47)
Rmin*AFTER		4.953		-6.171		-0.491 ***
		(0.12)		-(0.42)		-(3.49)
constant	4.598	6.102 ***	-9.142	7.247 ***	32.409 ***	6.202 ***
	(0.68)	(9.12)	-(1.36)	(9.55)	(3.53)	(8.64)
Lambda		-80.6		-0.2		-0.3
Standard error		-33.2		-2.7		-0.3
$H_0 \lambda = 0$		0.71		0.53		0.31
$H_0 \lambda = 1$		0.71		0.00		0.00
Lambda*AFTER		25.8		-1.2		0.2
Standard error		-114.6		-35.0		-0.3
$H_0 \lambda = 0$		0.91		0.71		0.32
$H_0 \lambda = 1$		0.91		0.49		0.00
Observations	562	562	507	507	496	496

Notes: All regressions include banks' fixed effects and robust standard errors. Robust *t* statistics are presented in parentheses. * significant at 10%; ** significant at 5%; *** signficant at 1%. The estimations are performed for quarterly data during the 1995-2002 period. Estimation is based on a seemingly unrelated (SUR) model. AFTER is a binary variable which takes the value one if the observation is on or after 2000. The interest rates refer to the new loans granted in each quarter. LC is a measure of local competition and POP is a measure of the importance of each market to bank i in period t. LC and POP are defined in Section 2.1. Cit is a measure of weighted funding costs, taking into account deposits and interbank funding. Rmin is a variable that measures the strategic interaction between banks, being defined as Rmin = (1/nbanks) * Ljt / Lit * (rjt - cjt), where Ljt and rjt are, respectively, the loan flow and the interest rates of each banks' rival, defined as that with the lowest interest rate in that quarter, in each market segment.

The t statistics for the coefficient associated with ln(rit) in columns (1), (3) and (5) are omitted, as this coefficient is determined by a constraint in the model. The lower number of observations in the regressions for households and firms is due to the fact that some small banks show null credit flows in one of these market segments in some quarters (two small banks never grant credit to firms during the entire sample period). Lambda reflects the effect of the rival banks on the profit maximization function of each bank and is derived from a combination of the estimated coefficients, resulting from the model.

The first row of the estimated coefficients in Table 5.3 shows the results for the variable $AFTER$. The negative coefficient in column (3) reveals that the quarterly credit flow decreased after the mergers for the household sector, despite the decrease in interest rates (column (4)). This suggests that there were important changes in market equilibrium after the mergers, given that a pure shift along the demand curve would imply a positive effect on credit due to the decrease in interest rates. We conducted some estimations that suggested that the decrease of loan flows to the household sector after the merger were mainly concentrated in loans for consumption and other purposes. For the corporate sector, the sale of credit increased after the merger, as observed in column (5), and the interest rate charged decreased, as shown in column (6)[101]. Post-merger equilibrium loan rates decrease when the merger induces large cost advantages relative to the increase in banks' market power, as shown by Carletti et al. (2007). Our results are consistent with Fonseca and Normann (2008), who argue that even though a merger involving the largest firm in

[101] To explore in more detail the timing of these effects, we estimated another modified version of our empirical model where instead of $\alpha_{01}AFTER$ and $\beta_{01}AFTER$ we consider $\alpha_{01}AFTER*D2000+\alpha_{02}AFTER*D2001+\alpha_{03}AFTER*D2002$ and $\beta_{01}AFTER*D2000+\beta_{02}AFTER*D2001+\beta_{03}AFTER*D2002$. This analysis shows that the negative effect on credit granted to households was gradual, but became slightly larger over time. In turn, the positive effect on loans to firms was concentrated in the immediate post-merger period. For interest rates, the decrease attributable to mergers was gradually felt over time, both for households and for the corporate sector.

a market creates a more asymmetric market structure, asymmetric markets exhibit lower prices than symmetric markets with the same number of firms.

In order to confirm the validity and strength of these differential impacts, we tested for the existence of a structural break after the merger wave, using a Chow test. In all the tests performed we reject the null hypothesis of structural stability of the parameters. These results show that the coefficients estimated for the entire sample period in Section 5.4 were inaccurate, as the merger wave had a relevant impact on credit flows and interest rates.

For robustness purposes, we considered the possibility that the effect of bank mergers takes some time to be reflected in credit flows and interest rates. To test this possibility, we estimated the same regressions, but considering that the dummy variable $AFTER$ would take the value of unity only from 2001 onwards. The results for households remain broadly unchanged. For firms, we continue to observe the negative impact on interest rates, but the positive impact on credit ceases to be significant. Nevertheless, the impact of the mergers should have been felt almost immediately, as suggested by the rapid change in banks' names and identities. To test the hypothesis that the merger impact could have had immediate impacts, we also estimated these regressions with the dummy variable $AFTER$ taking the value of unity from 1999 onwards. We observe that, in this situation, the differential impact of the merger wave on credit flows looses significance, thus confirming 2000 as a sensible break point.

Looking at the effect of local branch competition, we find that the impact was most significant for the corporate sector. In this credit market, we find that the merger leads to a decrease in the impact of local competition on the credit flow. Hence, the positive impact of local bank competition on credit granted to firms becomes slightly smaller (though still positive and large) after the merger wave.

The strategic effect of the main rival following the merger is presented in the last two groups of rows in Table 5.3. In what concerns the market for household loans, we clearly reject the hypothesis of collusion, though that conclusion does not hold for the post-merger period. In turn, in the corporate loan market we always reject the existence of full coordination moves between banks, even though λ increased somewhat after the merger wave.

5.5.2 Counterfactual Analysis of the Merger Wave

The previous analysis computes a differential effect of specific variables and assumes that all remaining interactions remain constant. However, this analysis does not fully take into account the structural changes that should have occurred in credit markets after the merger wave. Given the magnitude and extension of the mergers, the way banks (and their costumers) interact should have changed substantially after the merger. In this section, we assume that a new scenario is created that influences all variables in the credit market. Under this scenario, the evaluation of the differences in strategic effects requires the comparison between the results for the post-merger period and the ones obtained from the estimation of the pre-merger equilibrium using the post-merger data (counterfactual). The main advantage is that we can analyze the merger impact using the post-merger environment, which is obviously a much more realistic assumption.

The way we construct the counterfactual for the empirical estimation is the following. We first estimate the model (5.3) for the 1995-1999 period and obtain estimates for the pre-merger period. We then use the pre-merger coefficient estimates of this model for the 2000-2002 data on exogenous variables to obtain the value of the estimated post-merger credit flows and interest rates charged by the bank.[102] This means that these two estimated variables are the credit and interest rates in the post-merger period assuming the impact of the market environment, strategic effects and local market competition in the pre-merger period.

We also consider the possibility of ignoring changes in the branch network

[102] Given the recursive nature of the model, the estimated interest rates are used to estimate credit flows in the counterfactual.

after the mergers, given that the mergers should have had effects on the structure of the branch network and, most notably, on local bank competition. Hence, we also estimate counterfactual values for credit and interest rates by assuming that the branch network remains unchanged at pre-merger levels.

Counterfactual estimates of credit and interest rates Table 5.4 presents the main counterfactual estimations. The Table is divided in two panels. In Panel A we present the global results, while in Panel B we show separate results for two groups of financial institutions: (i) the ones that are directly involved in the merger wave and (ii) the ones that are not directly involved in the merger wave. By "directly involved" we mean that the financial group acquired or sold a financial institution to a different financial group.[103]

[103] As previously documented, out of the seven major financial groups, four were directly involved in the merger wave and three were not directly involved.

Table 5.4 - Analysis of credit flows and interest rate levels in different scenarios - counterfactual

Panel A

	All banks			
	Observed in the pre-merger period	Observed in the post-merger period	Estimated for the after-merger period (without merger effect)	Estimated for the post-merger period (keeping branch network at pre-merger levels)
	(1)	(2)	(3)	(4)
Credit flows (ln)				
Total	5.76	5.81	5.93	4.72 ***
Households	4.10	4.77	5.26 ***	4.97 *
Firms	5.59	6.01	4.36 ***	3.86 ***
Interest rates				
Total	11.46	8.20	9.53 ***	9.53 ***
Households	13.31	9.37	11.08 ***	11.08 ***
Firms	11.03	6.83	8.92 ***	8.92 ***

Panel B

	Banks directly involved in mergers				Banks not directly involved in mergers			
	Observed in the pre-merger period	Observed in the post-merger period	Estimated for the after-merger period (without merger effect)	Estimated for the post-merger period (keeping branch network at pre-merger levels)	Observed in the pre-merger period	Observed in the post-merger period	Estimated for the after-merger period (without merger effect)	Estimated for the post-merger period (keeping branch network at pre-merger levels)
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Credit flows (ln)								
Total	5.50	5.76	5.33 *	3.98 ***	6.16	5.88	6.68 ***	5.65
Households	3.74	5.07	5.13	4.93	4.60	4.37	5.44 ***	5.02 ***
Firms	5.39	6.14	3.92 ***	3.26 ***	5.84	5.89	4.79 ***	4.43 ***
Interest rates								
Total	12.18	8.92	10.71 ***	10.71 ***	10.39	7.30	8.06 ***	8.06 ***
Households	14.49	10.46	12.34 ***	12.34 ***	11.68	7.96	9.46 ***	9.46 ***
Firms	11.30	6.58	9.74 ***	9.74 ***	10.68	7.07	8.14 ***	8.14 ***

Notes: The estimations are performed for quarterly data during the 1995-2002 period. The pre-merger period comprehends the 1995-1999 period, whereas the post-merger period goes from 2000 to 2002. The group of financial institutions directly involved in the merger includes institutions belonging to financial groups that have acquired or sold a financial institution to a different financial group in 2000. The interest rates refer to the new loans granted in each quarter. Columns (3), (7) and (11) present the counterfactual estimates for the post-merger period, by taking into account the pre-merger equilibrium and the post-merger environment.Columns (4), (8) and (12) present similar counterfactual estimates for the post-merger period, with the difference that the branch network is assumed to remain unchanged at pre-merger levels. Asterisks refer to mean comparison tests between the counterfactual and the observed post-merger variables. * significant at 10%; ** significant at 5%; *** signficant at 1%.

We begin by directly comparing observed credit flows and interest rates in the pre- and post-merger periods. After the merger wave, loan flows were higher than in the pre-merger period, both for households and firms. It is worth noting that this trend was stronger for the banks directly involved in the mergers, given that the remaining banks actually recorded some decrease in loan flows, especially in what concerns loans to households. Comparing interest rates in the pre- and post- merger periods, we observe that there was a widespread decrease in interest rates after the mergers occurred, partly reflecting lower banks' funding costs arising from lower money market interest rates during this period, as well as from access to more varied funding sources due to the integration in the European Monetary Union. However, the data clearly show that banks directly involved in the mergers decreased interest rates more aggressively than the other banks, narrowing their interest rate margins in order to attract more customers and, possibly, also reflecting efficiency and informational gains arising from the merger process[104] (see, for example, Sapienza, 2002, Hauswald and Marquez, 2006, Panetta et al., 2009, and Erel, 2011).

In columns (3), (7) and (11), we present the counterfactual estimates of loan flows and interest rates. As described above, these estimates result from predicting these two variables for the post-merger period, by taking into ac-

[104] These efficiency gains are expected to be larger when there is a significant market overlap between merging banks. Indeed, this is the case in our sample, where merging banks are large universal banks operating throughout the whole country in most retail segments. It is thus reasonable to argue that the restructuring of overlapping branch networks and business segments may have contributed to efficiency gains.

count the pre-merger equilibrium and the post-merger environment. Hence, variables such as money market interest rates, GDP or number of branches are considered in the post-merger period to obtain these estimates. In these columns we also present the results of mean comparison tests between the counterfactual estimates and the post-merger observed variables.

By comparing credit flows observed after the merger with the estimated post-merger flows, we conclude that loan flows would have increased even more if mergers would not have occurred. When total credit flows are considered, the difference between the counterfactual and the actually observed loan flows is not statistically significant, except for the banks that were not directly involved in the merger wave. In fact, the latter recorded a decrease in credit granted after the merger wave that would not have occurred if the mergers had not taken place, according to the counterfactual estimates. This result demonstrates that mergers induced important market shifts, with merging banks gaining market share.

Our results show that there are important differences between the evolution of loans to households and to firms[105]. On the one hand, the model predicts that household credit could be larger than what was actually observed (especially for the banks not involved in the merger wave). On the other hand,

[105] These differences may have important economic implications, as shown by Beck et al. (2009).

the model predicts a slowdown in credit granted to firms, in striking contrast with the acceleration actually observed during this period. The difference between estimated and observed corporate loans was larger for the banks directly involved in the merger wave.

The counterfactual estimates also suggest that interest rates would still decrease if no mergers had occurred. However, comparing these estimates to the post-merger observed values, we conclude that the observed decrease in interest rates was, by any means, larger than that predicted by the pre-merger equilibrium, even taking into account the developments in money market interest rates in the post-merger period. The most impressive difference comes from the interest rate on loans to firms applied by the banks involved in the merger wave, which may suggest efficiency and informational gains arising from these mergers.

Finally, in columns (4), (8) and (12) we present the results for the counterfactual estimates when the branch network is assumed to remain unchanged at the pre-merger levels. This may be a strong assumption, given that it is unlikely that the branching structure and the intensity of local bank competition would not change between 1999 and 2002. However, without the mergers this branching network would probably be considerably different from the one actually observed, thus making these results relevant for this counterfactual estimation. In this version of the counterfactual, interest rates would be the same as in the previous counterfactual estimation, given that the model establishes that the number of branches does not directly affect interest rates charged by banks (see equation 5.3)[106]. However, in what concerns loan flows, the estimates show that if there were no changes in the branch network, the estimated loan flows would not be as large as predicted by the counterfactual that assumes changes in branches. This result is especially strong for corporate loans.[107]

This table also allows us to compare the counterfactual outcome for banks involved and not involved in the merger wave. The predicted increase in loan flows to households would be higher for the banks not directly involved in the merger wave (assuming that these mergers had not occurred). However, this difference is not statistically significant, when predicted loan flows for these two groups of banks are compared. In turn, the decrease in loan flows to firms

[106]In these columns, the interest rates, loan flows and the strategic interaction variable were computed using the values predicted by the model, instead of using directly the values observed. The results are consistent under both hypotheses.

[107]For robustness purposes, we conducted several sensitivity tests on the definition of the post-merger period (as done for the analysis of the differential impact of the merger wave). More specifically, we consider the possibility that the effect of bank mergers takes some time to be reflected in credit flows and interest rates. Moreover, it is also possible that immediately before the merger there were some strategic effects. To take all this into account, we exclude the last two quarters of 1999 and the year 2000 from our estimations. The results are qualitatively robust. The effect of bank mergers on total credit flows is slightly less significant for the banks directly involved in mergers, but more significant for the whole sample.

predicted by the counterfactual would not be so large for the banks not involved in the merger (with this difference being statistically significant), thus suggesting some market shifts induced by the mergers. Finally, the counterfactual predicts that the interest rates charged by the banks involved in the mergers would always be significantly higher than for the banks that did not have an active role in this process, even though after the merger the interest rates charged by the banks involved in loans to the corporate sector became lower than in the other group of banks, thus confirming possible efficiency gains for the banks that merged.

A decomposition of merger impacts using counterfactuals Using these counterfactual estimates, we can decompose the merger impacts into several different components, distinguishing between changes in the exogenous environment and changes in the branch network and market structure. This decomposition is presented in Table 5.5.

Table 5.5 - Decomposition of merger impacts using counterfactual analysis

Panel A — All banks

	Changes in exogenous environment (macroeconomic and financial conditions) (1)	Changes in branch network and market structure (2)	Other structural changes and prediction error (3)	Total effect (4)
Credit flows (ln)				
Total	-1.04	1.21	-0.12	0.05
Households	0.87	0.29	-0.50	0.67
Firms	-1.73	0.51	1.65	0.42
Interest rates				
Total	-1.93	0.00	-1.33	-3.26
Households	-2.23	0.00	-1.71	-3.95
Firms	-2.11	0.00	-2.09	-4.20

Panel B

	Banks directly involved in mergers				Banks not directly involved in mergers			
	Changes in exogenous environment (macroeconomic and financial conditions) (5)	Changes in branch network and market structure (6)	Other structural changes and prediction error (7)	Total effect (8)	Changes in exogenous environment (macroeconomic and financial conditions) (9)	Changes in branch network and market structure (10)	Other structural changes and prediction error (11)	Total effect (12)
Credit flows (ln)								
Total	-1.52	1.36	0.42	0.26	-0.51	1.03	-0.80	-0.28
Households	1.20	0.19	-0.06	1.33	0.42	0.41	-1.06	-0.23
Firms	-2.14	0.66	2.22	0.74	-1.42	0.36	1.11	0.05
Interest rates								
Total	-1.47	0.00	-1.79	-3.26	-2.33	0.00	-0.76	-3.09
Households	-2.16	0.00	-1.87	-4.03	-2.21	0.00	-1.51	-3.72
Firms	-1.56	0.00	-3.16	-4.72	-2.54	0.00	-1.07	-3.62

Notes: The estimations are performed for quarterly data during the 1995-2002 period. The pre-merger period comprehends the 1995-1999 period, whereas the post-merger period goes from 2000 to 2002. The group of financial institutions directly involved in the merger includes institutions belonging to financial groups that have acquired or sold a financial institution to a different financial group in 2000. The interest rates refer to the new loans granted in each quarter. The change in exogenous environment (1) is the difference between the estimated value for the after merger period keeping the branching network at pre-merger levels and the value predicted for the pre-merger period. The change in the branch network (2) is the difference between the values estimated for the post-merger period with and without changes in branches. Other structural changes (3) are the difference between the values estimated and observed for the after merger period. The total effect (4) is the sum of all the previous effects, being the difference between the values observed after and before the merger wave.

In columns (1), (5) and (9) we present the effect of changes in the exogenous environment on loan flows and interest rates, for the three groups of banks under analysis. This effect is computed as the difference between the counterfactual estimates for the post-merger period when holding the branch network and market structure at pre-merger levels, but taking into account changes in macroeconomic and financial conditions after the merger wave (columns (4), (8) and (12) in Table 5.4). In what concerns interest rates, the effect was clearly negative and close to 2 p.p. Hence, a considerable part of the decrease in interest rates in the post-merger period was due to changes in macroeconomic conditions. Regarding loan flows, changes in banks' economic and financial environment led to an increase in loan flows to households and to a decrease in loan flows to firms. As discussed above, this result means that the counterfactual estimates without changes in branches suggest that loans to households should have been higher if the mergers had not occurred (the opposite being true concerning loans to firms). The impact of the changes in the macroeconomic and financial environment on loan flows was stronger for the banks directly involved in the merger wave.

When changes in the branch network and in local market competition are considered (columns (2), (6) and (10)), we observe a positive impact in loan flows, when compared to the impact of considering only changes in the exogenous environment. These estimates correspond to the difference between columns (3) and (4) in Table 5.4, i.e., the difference between the counterfactuals with and without changes in branches. Hence, when changes in the branching network observed after the merger wave are considered, we conclude that loan flows should have been even higher if mergers had not occurred. This difference assumes a larger magnitude in loans to firms. As previously discussed, interest rates estimates remain unchanged, given that they are not directly influenced by the number of branches in our structural model.

Finally, we present the estimates for the impact of other structural changes (which includes a prediction error), defined as the difference between interest rates and loan flows observed after the merger wave and the counterfactual estimates (with changes in the branch network), for these variables. In other words, these estimates represent the merger impact that is not accounted for by the change in the macroeconomic environment neither by the change in market structure. For interest rates, this impact is negative and larger for the banks directly involved in the merger wave, thus showing that these banks decreased interest rates more aggressively after the merger than what would have been predicted by the model if mergers had not taken place. In what concerns loan flows to households, we obtain a similar result: these flows were lower after the merger than what is predicted by the counterfactual analysis. In contrast, loan flows to firms were higher than those predicted by the counterfactual estimates, as previously discussed, especially for the banks directly involved in the merger wave.

Main counterfactual results In sum, we observe that mergers have increased the amount of credit granted to firms and decreased the availability of loans to households. Moreover, the merger wave induced a stronger decrease in interest rates than what could have been expected, thus benefiting consumers. By decomposing the merger impact, we conclude that the decrease in interest rates was mainly explained by changes in banks' macroeconomic environment, even though the merger wave contributed to intensify this decrease. The increase in loan flows to households after the merger was mainly explained by changes in the macroeconomic environment, given that structural changes generated by the mergers had a negative effect on loan flows to households. Finally, the increase in loan flows to firms in the post-merger period can be mostly explained by structural changes generated by the mergers, as macroeconomic changes would have implied a deceleration in loans to firms during this period.

These results are broadly consistent with those resulting from the differential analysis of the merger wave impacts, even though that would not necessarily have to be the case. The counterfactual analysis provides a much more rigorous and detailed framework to disentangle the merger impacts, by relying on a structural model of equilibrium. In turn, the reduced form differential approach allows only analyzing how aggregate market outcomes change after the merger occurs. The structural analysis derived from the counterfactual scenario is incomparably richer, allowing to clearly disentangle changes in market structure and conduct from changes in the macroeconomic and financial environment.

5.6 Concluding remarks

Bank mergers usually have important consequences in terms of bank competition, access to credit or loan pricing. However, the effects of bank mergers on these variables are hard to disentangle from other market and macroeconomic dynamic effects that occur simultaneously, affecting loan demand and supply, as well as its pricing. In this chapter, we present a structural analysis of the impact of mergers in the Portuguese banking market. In the late 90s, several large banks were involved in a strong and fast consolidation process, thus providing an empirical setup to assess changes in market structure after the mergers.

Using a structural model, we derive the equilibrium in the pre-merger setting. Combining this estimated equilibrium with the post-merger environment, we are able to construct a counterfactual estimate of loans and interest rates. This allows us to compare the observed loan flows and interest rates with those resulting from the pre-merger equilibrium, thus assessing the impacts of the bank merger wave. Moreover, the counterfactual estimation allows for taking into account changes in conduct and market structure after the mergers take place. These effects are usually ignored in the assessment of merger impacts and may lead to a significant bias in the results obtained.

We obtain several interesting results. The interest rates observed after the mergers were lower than those predicted by the model, in the pre-merger equilibrium. This may reflect efficiency and informational gains resulting from the mergers and translated into more competitive pricing. In turn, there are important differences between loans granted to households and to firms: whereas loans granted to households were in fact lower than what would be suggested using the pre-merger equilibrium, loans granted to firms actually recorded a stronger growth than what could have occurred if no mergers had taken place. All in all, households may have faced some constraints in access to credit after the merger, even though loans to households recorded robust growth rates during this period. On the contrary, loans granted to firms seem to have surpassed by a large extent the counterfactual estimates.

The counterfactual estimates also highlight important differences between the banks directly involved in the merger wave and the remaining large banking groups. The banks directly involved in this process decreased their interest rates on corporate loans much more aggressively than other banks. Simultaneously, credit granted to firms by these banks was also much larger than what could have been expected if no mergers had occurred. In turn, the estimated decrease of loans granted to households assumed a larger magnitude for the banks that did not directly participate in the merger wave.

By decomposing the merger impacts through the use of the counterfactual estimates, we conclude that changes in banks' macroeconomic and financial environment were the main driving force when explaining the differences in interest rates and loan flows before and after the merger wave. Structural changes generated by the mergers contributed to intensify these changes in loans and interest rates on firms, but had the opposite impact on loans to households.

The structural model used to perform these counterfactual estimates allows for clear identification of the effects of bank mergers on credit and interest rates, isolating changes in the exogenous environment and in market structure. Changes in market equilibrium resulting from the mergers affect significantly banks' decisions, as well as their strategic interactions, thus demonstrating the importance of relying on a structural estimation method. All in all, we observe that potential efficiency and informational gains seem to have been transmitted to customers through lower lending rates and firms have faced less bank financing constraints than they otherwise would.

6 Dutch summary

In dit proefschrift onderzoek ik verschillende dimensies van risico in de bankensector en de gevolgen van risico voor de toegang van bedrijven tot krediet. De wereldwijde economische en financiële crisis heeft duidelijk gemaakt dat een stabiel en goed functionerend banksysteem een belangrijke pijler is voor economische groei. In deze context tracht ik in de vier hoofdstukken van dit proefschrift licht te werpen op cruciale punten die van invloed zijn op de stabiliteit van het financiële stelsel en uiteindelijk op de algehele economie.

Ten eerste, in hoofdstuk 2, beschouw ik de rol van strategische interacties in het nemen van risico en richt mijn studie op liquiditeitsrisico. Individueel gezien optimaliseren banken het beheer van het eigen liquiditeitsrisico, waarbij vaak de gevolgen voor het totale risico van het financiële stelsel worden verwaarloosd. Dit is het belangrijkste argument om de regulering van liquiditeitsrisico te ondersteunen. Bepaalde stimulansen voor banken kunnen er echter toe leiden dat banken deelnemen aan collectieve risico strategieën die het systeem risico doen toenemen, bijvoorbeeld door de aanwezigheid van een "Lender of Last Resort". In dit hoofdstuk ga ik op zoek naar bewijs voor coördinerend gedrag in het nemen van risico's door banken en richt mij tot de periode van vóór de wereldwijde financiële crisis. Ik vind eenduidig en robuust bewijs voor coördinatie in het beheer van liquiditeitsrisico van banken en houd rekening met mogelijke endogeniteit. Dit probleem wordt met name veroorzaakt door de wederkerige aard van de beslissingen die genomen zijn door banken. Het resultaat suggereert dat de prikkels voor het collectief nemen van risico's een rol speelt in de keuzes van banken en pleit voor een macro-prudentiële aanpak van de regelgeving van liquiditeitsrisico.

In hoofdstuk 3, onderzoek ik een andere dimensie van bankrisico, namelijk de invloed van de macro-economische omstandigheden op kredietrisico. De aard van kredietrisico wordt hetzij voornamelijk gedreven door bedrijfsspecifieke kenmerken ofwel door systematische factoren. Het verschil in de mogelijke oorzaak van kredietrisico is een belangrijke kwestie in de analyse van de financiële stabiliteit. Door het verkennen van de verbanden tussen kredietrisico en macro-economische ontwikkelingen neem ik tijdens perioden van economische groei een tendens tot het nemen van buitensporige risico's waar. Met behulp van een uitgebreide dataset welke gedetailleerde informatie bevat voor meer dan 30.000 bedrijven, laat ik zien dat de kans op faillissement wordt beïnvloed door verschillende bedrijfsspecifieke kenmerken. Deze resultaten verbeteren aanzienlijk door rekening te houden met tijd-effecten en macro-economische variabelen. Alhoewel de financiële situatie van de ondernemingen een centrale rol speelt in het verklaren van de kans op faillissement zijn macro-economische omstandigheden ook belangrijk bij de berekening van deze kans in de loop van de tijd.

In hoofdstuk 4 onderzoek ik een verwante kwestie. Hoewel er een uitgebreide literatuur bestaat over de oorzaken van faillissement, is daarentegen bewijs beperkt over wat na het faillissement gebeurt met bedrijven. In dit hoofdstuk onderzoek ik wat er gebeurt met bedrijven nadat ze hun verplichtingen op bankleningen niet nakomen. Ik benader deze vraag door het creëren van een reeks van gestileerde feiten in relatie tot de evolutie van faillissementen en de daaropvolgende oplossing en leg de nadruk op de toegang tot krediet na het faillissement. Met behulp van een unieke dataset over Portugal, merk ik op dat voor de helft van de gevallen het faillissement wordt afgewikkeld binnen vijf kwartalen. De meeste bedrijven behouden toegang tot krediet onmiddellijk na het oplossen van het niet kunnen nakomen van de verplichtingen. Daarnaast heeft slechts een minderheid van de bedrijven daarna toegang tot nieuwe leningen. Kleine bedrijven hebben meer problemen met het herstellen van toegang tot krediet, met name: wanneer het faillissement lang en zwaar is; indien zij lenen van slechts één bank; of als verplichtingen met de belangrijkste geldschieter niet worden nakomen. Bovendien is het waarschijnlijk dat de helft van de bedrijven met huidige betalingsproblemen in de toekomst opnieuw in gebreke zal blijven. Ik merk dat bedrijven met herhaald verzuim van betaling gemiddeld genomen kleiner zijn en langer en heviger in gebreke blijven bij het betalen van crediteuren.

Tenslotte onderzoek ik in het laatste hoofdstuk een andere veel voorkomende gebeurtenis in het bankwezen die de stabiliteit van de banken kan beïnvloeden, evenals de toegang van ondernemingen en huishoudens tot krediet. Golven van bank fusies kunnen structurele veranderingen in het evenwicht van de kredietmarkten genereren waardoor prijzen en hoeveelheden veranderen in deze markten, met belangrijke gevolgen voor de concurrentie. Ik voer een zogenaamde counterfactual analyse uit voor bank fusies door het berekenen van het prefusie evenwicht en dit evenwicht te vergelijken met de post-fusie kenmerken. Hierbij houd ik rekening met endogene veranderingen in de marktstructuur. Met behulp van deze procedure ben ik in staat om de effecten in de stroom van leningen en in de rente te schatten. Deze stroom zou zijn waargenomen als het pre-fusie evenwicht niet zou zijn gewijzigd. Resultaten worden afzonderlijk verkregen voor bedrijven, huishoudens en banken voor situaties waar fusies zich wel voordoen, en niet voordoen. Ik ontdek dat fusies tot een betere toegang voor bedrijven tot krediet leiden, maar dat ze een tegenovergesteld effect op huishoudens hebben. Daarnaast leiden fusies tot een algehele daling van de rente.

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